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HUMAN OPERATOR CONTROL STRATEGY MODEL

By

Harold F. Engler
Esther L. Davenport
Joanne Green
William E. Sears, III

Georgia Institute of Technology
Engineering Experiment Station
Atlanta, Georgia 30332

ADVANCED SYSTEMS DIVISION
Wright-Patterson Air Force Base, Ohio 45433

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ROSS L. MORGAN, Technical Director
Advanced Systems Division

RONALD W. TERRY, Colonel, USAF
Commander

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Present measures of performance during training are inadequate for sensitively describing cue utilization, for assessing individual differences, and for predicting transfer of training to other tasks. The present research attempted to approach this problem by developing a computer simulation of continuous motor control learning, including a representation of control strategy, and applying the simulation to measurement of human control strategy. Initial demonstration and validation tests indicate that the simulation is able to identify aspects of human control strategy, and that such identification may provide a more sensitive measure of performance.

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PREFACE

This work was conducted under Project 2313-T5-20 (formerly 2313-T3-03), Contract F33615-77-C-0042, with Patricia A. Knoop serving as contract manager for the Air Force.

The research was conducted at the Engineering Experiment Station (EES) of the Georgia Institute of Technology under the technical supervision of Esther Lee Davenport, Research Engineer II, the direct administrative supervision of William E. Sears, III, Chief, Special Projects Division, and the general administrative supervision of Robert P. Zimmer, Director, Systems Engineering Laboratory. Financial contribution to the progress of this research from far-sighted persons in management roles at EES has been substantial. Funds for equipment on which to run the preliminary tests were committed by leadership including Robert P. Zimmer, Director, Systems Engineering Laboratory; Howard Dean, Associate Director of EES and Archie Corriher, Assistant to the Director, EES. Early phases of the project were under the supervision of David Clifton, Chief, Energy and Engineering Division, and the general administrative supervision of Rudy L. Yobs, Director, Technology and Development Laboratory.

Sincere thanks are due Pat Knoop, Advanced Systems Division, Air Force Human Resources Laboratory. She first conceptualized the approach taken here, and has been a continuing source of ideas and encouragement. Larry Reed, also of Advanced Systems Division, has provided many valuable insights during the course of work. Darwin P. Hunt, New Mexico State University, has also contributed considerable insightful commentary and criticism of the work.

Numerous persons in Systems Engineering Laboratory, other than the report authors, have provided helpful and, in some cases, essential support to the project. Andy Lipscomb was involved in early phases of the project. Frank Vogler has been a continuing resource during testing and analysis phases. Cooperative Plan students Kirk Hoyer, Bob Baltar, and Bob Hummel have each made major contributions to the innovative software required by the project.

Thoughtful contributions to the project have also been made by persons from other administrative units at Georgia Tech. Foremost among these are Ross Gagliano of the Radar and Instrumentation Laboratory and Tom Sadosky of the School of Industrial and Systems Engineering. Appreciation is also due Doug Davenport, of the School of Psychology, and to Gary Kelly, of the Economic Development Laboratory. Especially helpful from a technical standpoint during the trial runs of the experiment were discussions held with Archie Corriher, Assistant to the Director, EES, and with Sallie Daniell of the Economic Development Laboratory.

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SECTION I

INTRODUCTION

This research involved the development and testing of a computer simulation of motor skill learning. The work was unique in at least three respects. First, the simulation was designed to be consistent with psychological theory and data in its structure and processes. Second, the simulation includes representation of a construct called control strategy which is believed to affect motor learning and performance. Third, the simulation was used to measure control strategy in humans.

Control strategy was defined as a set of parameters selected by the human operator that determine the style of learning and performance in manual control tasks. The parameter set consists of:

1. The criteria for behavior in various aspects of the task.
2. The stimulus cues to guide performance.
3. The sequence for performance of decision-making processes important in manual control.

Why is control strategy a worthwhile subject for measurement? An extensive literature indicates that control strategy, if measurable, should provide a valuable supplement to conventional learning measures such as tracking error or time-on-target. This supplement is particularly necessary for the measurement of pilots' progress in training. Frequently, conventional measures fail to detect the effects of different cues provided to trainees, or fail to distinguish between trainees at different levels of skill (see Section IIA). Equipment and procedures for pilot training are expensive, and failure to provide adequate training can be life-threatening. Thus, the development of additional measures of human learning of manual control tasks such as flying has the potential for making a major impact on the cost-effectiveness of pilot training and on pilot safety. How, then, might measurement of control strategy provide useful information?

One reason that control strategy measurement may be informative is that the control strategy developed during training is believed to affect performance in the actual task setting. Further, it is believed that while different control strategies may result in quite similar performances during training, they may result in quite different performance levels in the actual task setting (see Section IIIE). Thus, direct measurement of control strategy and understanding of its relation to performance in tasks other than the training task could be quite valuable in the design of effective training programs.

A second potential contribution of control strategy measurement is for the training of individuals in the use of effective control strategies. The literature indicates that control strategy learning is influenced by several factors - previous experience with tasks similar to one currently being trained, direct experience in the task being trained, and the functioning of attentional processes related to the general performance of the operator. Since control strategy is learned not only through present experiences, but also from past experiences unique to the operator, it follows that the control strategy which develops for a given task will vary between individuals. The strategy that develops may or may not be the most effective one for a task. Therefore, the possibility exists that there can be explicit training for good control strategies--good, in the sense that the control style developed is effective not only for training, but also for actual performance. Flight training might then be accomplished in a shorter time than is now possible or with fewer, better selected cues. Flight simulator design might be considerably aided by detailed knowledge of necessary cues. Thus, there are a variety of reasons for believing that control strategy is important and a worthwhile object for measurement.

Measurement of the time-varying control strategies of human operators was accomplished in this project by use of a computer simulation. The simulation contained a representation of control strategy as defined previously, permitted control strategy to be varied, and reflected psychological evidence about human information processing in motor skill learning. A major part of the work involved the development of the simulation. This required the synthesis of a theory of strategy-controlled learning in manual control tasks (see Section III). The theory was based on a review of the existing literature but also includes several novel ideas which merit testing in themselves.

The theory guided the development of the computer program called the Human Operator Performance Emulator, or HOPE (see Section IV). Given a numerical representation of a track, HOPE predicts control stick positions that a human operator would use to align a cursor in a preview tracking task. The operation of the HOPE program is modulated by a set of three variable value control strategy parameters, which represent the ways that different control strategies affect human information processing and performance.

Measurement of control strategy in humans is accomplished by a three step procedure. First, different sets of values of the control strategy parameters are specified for HOPE. Second, the modulation of HOPE by each set of parameter values results in multiple HOPE models of human learning and behavior. Each model predicts human behavior guided by a particular control strategy. Finally, the predictions of the different models are compared to human behavior in a particular training condition. The values of the control strategy parameters of the model which best predict the individual's behavior in a specified time frame are used to infer human control strategy (see Section VB5).

HOPE has received preliminary demonstration and validation tests, the methods and outcomes of which are described in Section V. The results of these efforts are most encouraging, and support the HOPE representation of human control behavior and control strategy. HOPE is able to predict human behavior to a considerable extent. Human control strategy, as identifed by HOPE, varies as is predicted by psychological theory--it changes with learning, reflects differences between training conditions, and varies between individuals. The results suggest that HOPE has considerable potential for providing valuable information about human control strategy and about the progress of human learning.

SECTION II

THE MEASUREMENT PROBLEM IN FLIGHT TRAINING AND RATIONALE FOR THE RESEARCH APPROACH

This section includes (a) a description of the primary problem which stimulated this research, (b) a rationale for selecting control strategy as a subject for measurement, (c) a rationale for rejection of mathematical modeling approaches to the measurement of control strategy, (d) a description of the psychological modeling approach taken in this project, and (e) a summary of the major points made in the section.

A. The Problem

Continuous manual control is of fundamental importance to a number of human activities. Vehicular control, in particular, involves continuous manual control in the form of tracking. This requires the execution of a smooth sequence of accurate movements in response to a presented pattern, such as a road or flight maneuver profile. Because of the importance of this class of perceptual-motor skills, tracking has been the subject of many studies, particularly in the area of flight simulation research.

Flight simulation research should include identification of the necessary and sufficient cues to be included in simulators used in flight training. Development of simulators can aim at full physical fidelity with the actual flight environment. However, this may not be a cost-effective approach if pilots do not, in fact, use all the cues present in their environment. A more cost-effective approach would be to identify and include in simulators only those cues which actually affect learning and transfer to real flight behavior. This requires accurate and sensitive measures of the effects of various cues or combinations of cues on human learning in order to identify a minimum set of cues.

However, as Knoop (1978, p.8) points out, existing measures of human performance in continuous control tasks "do not have the necessary characteristics to support the type of flight simulation research that entails accounting for the perception and utilization of cues." Traditional measures, such as average absolute error, root mean square error, or time on target are sometimes inconsistent in the ways they change in response to experimental manipulations (Obermayer, Swartz, & Muckler, 1962). Several commonly used measures are not Gaussian in their distributions, and thus frequently used parametric statistics are not appropriate (Poulton, 1974).

Most importantly, traditional measures tend to obscure differences in details of behavior of persons at different skill levels. Two individuals may appear to be at the same level of skill at the end of train-

ing, yet one may perform much better than the other under the stresses of actual flight. Furthermore, traditional measures do not specify the differences in the outcomes of different training conditions, yet these subtle differences may be most important, particularly for transfer to actual flight performance. Traditional measures assess mainly overt performance, and do not provide information about important cognitive changes in individuals that may occur during training.

Thus, it is important to develop better measures of performance during flight simulation and other types of training for at least three purposes:

1. To better describe the effects of different training cues.

2. To better distinguish between individuals in different levels of skill.

3. To better predict the transferability of skills attained under different training conditions.

B. Control Strategy as a Subject for Measurement

The preceding discussion highlights the need for a new approach to measuring continuous control task performance. For application to flight simulation training, the new approach should describe cue utilization, should highlight differences between persons at different skill levels, and should aid in the prediction of actual flight performance. The present investigation is based on the assumption that measurement of the control strategy developed during training might provide an informative description of the outcomes of training, one which could substantially add to the information provided by conventional performance measures.

1. Definitions of Strategy

A variety of aspects of perceptual and motor skills have been termed strategy. For example, Welford (1968) considers strategy to be a learned skill which develops with practice and which varies between individuals far more than do conventional error measures. More specifically, the term strategy has been said to determine the way in which people choose to use information during task performance, and is reflected in behaviors such as the following:

a. the use of warning signal information in choice reaction time tasks (Alegria, 1975).

b. the pattern of sampling auditory information (Moray, 1975).

c. the use of preview information to reduce reaction time (Welford, 1968).

d. the pattern of memory search (Welford, 1968).

e. the ability to systematically seek task information (Welford, 1968).

f. the speed-accuracy tradeoff that results from a particular set of instructions or pay-offs (Ollman, 1977).

In summary, strategy is viewed by many researchers as a construct which determines what environmental information gets used, and what control actions are taken.

Of particular interest to the present discussion are suggestions that strategies for performance develop during training and affect the quality of later performance. As was mentioned, Welford (1968) considers strategy to be a learned skill, which varies among individuals. He believes that the specific strategy used by an individual depends on the timing and location of cues for performance. Poulton (1974) suggests that different training conditions produce different strategies. Although he does not define what he means by strategy, he says that the diversity of the experimental tracking literature can be understood with the aid of this concept. For example, the effects of different strategies are manifested in asymmetrical transfer, a phenomenon whereby the effect of a given training condition may differ depending on whether it comes before or after another different training condition. The appearance of asymmetrical transfer suggests that the performance transfer to a task depends upon the strategies developed in prior training. Welford's ideas bolster the argument that measurement of control strategy in flight simulation training may be useful for predicting real flight behavior.

2. Strategy During Tracking

How might control strategy affect tracking? First of all, it must be recognized that although tracking appears as a unified behavior, a variety of information processing activities are involved, each of which might be modulated by an individual's control strategy. For example, although performance monitoring occurs continuously, an individual's control strategy might determine how much error is allowed before special effort is devoted to correcting errors. In conditions of flight, strategy might determine how often the "track" (i.e., desired path of flight) is sampled, and how attention is divided between the numerous information sources which must be monitored. Strategy might affect the frequency and direction of motor commands, thus determining whether movements appear as short and ballistic, or longer and smoother in quality. Strategy might affect whether excessive error is responded to in a conservative way, in the form of small motor movements, or in a bolder, more aggressive fashion. These ideas lead us to define control strategy as a set of decisions affecting human cognitive control processes. This definition is detailed in Section III.

In summary, it appears that tracking is a behavior which is a likely candidate to be affected by an individual's control strategy. The characteristics of control strategy are that it is learned, differs between individuals, and affects performance on other tasks. Because of these characteristics, the measurement of control strategy may be a useful approach for predicting the results of different conditions in flight simulation training.

C. Weakness of Existing Modeling Approaches to Strategy Measurement

Measuring the development of control strategy in continuous control tasks poses a significant challenge. In order for the measures to be useful, they should be valid, reliable, objective, descriptive of the psychological effects of various training procedures, and predictive of human behavior in transfer to related tasks. Furthermore, the concept of control strategy must be defined precisely enough so that it can be measured.

One approach to measurement is to develop a model of the human behavior of interest. As Knoop (1978, p. 12) points out, "often the most concise way to represent a set of data...is to model the process that generated it. If modeling techniques were applied to human performance measurement, it is conceivable that an optimally concise set of measures could be derived from the model itself." A variety of researchers (McRuer & Krendel, 1974; Pew & Rupp, 1971; Hess, 1977) have argued for the use of mathematical models to provide insight into the effect of various cues on skill acquisition. These writers consider the parameters of the mathematical models as possible candidates for measurement of human response to cues.

However, the usefulness of applying current mathematical models to the measurement of human control strategy and cue utilization is questionable. Knoop (1978) provides an extensive review of these models and concludes that most do not reflect certain important characteristics of the psychological make-up of the human operator and therefore may not be valid for the purpose of measuring human performance. To quote Knoop (p. 65):

> "Existing models were categorized by type as follows: (1) Describing Functions; (2) Optimal Control Model; (3) Discrete and Finite State Methods; (4) Adaptive Techniques; (5) Preview Models; (6) Other Nonlinear Approaches. A survey was made of models in each category by reviewing the literature and summarizing the various modeling studies. Particular attention was devoted to modeling assumptions and whether or not any specific human operator characteristics were incorporated.
>
> "Models in each category were evaluated based on the extent to which they represent the identified human operator characteristics as well as other aspects of their general validity for per-

formance measurement applications. It was found that none of the models reviewed implement more than a few of the operator characteristics; and those which do are either based on other assumptions which are unacceptable for measurement applications or have not been far enough developed to justify their use as a point of departure. The major reason for this is that existing models were not developed with measurement as an objective; and the attempt has been to emulate human output rather than simulate or otherwise account for the intricacies of human behavior.

"It is concluded that existing human operator models are not sufficiently representative of known characteristics of human behavior to be useful for general performance measurement applications. It appears, too, that modeling studies of the past have emphasized matching the response of the average human operator at the expense of modeling the behavior of the individual."

The psychological characteristics which Knoop (1978, p. 28) believed important to include or otherwise account for in models were operator intermittency, the psychological refractory period, the range effect, inadvertent cross-coupling, bang-bang control, and varying cue utilization. Other characteristics that should be considered, according to Knoop, are "the existence of observation and control errors, time variations in control strategy, threshold and saturation effects, preview and precognitive functions, variations in performance due to changes in attention and fatigue, and, generally, man's ability to remember, predict, reduce information, and make decisions."

Another important characteristic of human beings is the ability to learn, an ability which is of major interest in the measurement of the effects on control strategy of variations in training conditions. To learn is to gain knowledge or mastery through experience; to learn is to exhibit a change in behavior because of exposure to experience, a change not due to maturation, fatigue, motivation, illness or injury. Some attempts have been made to model the learning process through the use of mathematical models which store the results of past control actions and use the information to determine current actions. For example, Preyss and Meiry (1967) and Meiry (1968) developed a model to control a two-position switch to drive an initial displacement in one dimension to zero. Bayesian statistics were used to update the control memory after the result of a switching action is observed. Thomas and Tou (1966) proposed a model that 'learns' to reach some pre-specified final state, under cost constraints, by remembering the costs associated with each move in the environment. The models are interesting because they exhibit intelligent behavior. Models of this type are not designed, however, to be psychologically valid; and thus the possibility of representing human control strategy in any of these models appears very remote. They are not suitable for application to measurement of strategies developed by humans in the learning process.

Kelley (1967) made three summary criticisms of mathematical models of the human controller. They are:

(1) Input to the model is severely impoverished compared with input to an actual human operator. Input is often restricted to a one-dimensional, point-in-time error measure assumed to be obtained visually. In fact, human operators use multiple cues obtained through a variety of sensory channels.

(2) The model is limited to control action based on input at a point in time. Actual human operators, however, may base their control actions on remembered results and expected results as well as on instantaneous error.

(3) The model contains no internal representation of the task, only a rule for acting on the input. The human operator is aware of the task and free to redefine the task if, by doing so, the objective may be better accomplished.

As Knoop (1978) points out, certain forms of the optimal control models, finite state models, or other probabilistic models do not suffer from the first or second of these objections. However, all existing models have weaknesses that make infeasible their application to measurement of control strategy. In view of the weaknesses of these models, the decision was made to seek another approach to modeling the important aspects of control strategy.

D. Psychological Simulation Approach to Control Strategy Measurement

The literature discussed previously suggested that the following characteristics of control strategy were worthy of understanding: its dependence upon training, its variation between individuals, its effects on the learning and performance of continuous motor control, and its predictive value. The processes that generate human control behavior are largely unobservable processes, governed in large part by control strategy. As observed previously, Knoop (1978, p. 12) pointed out, "often the most concise way to characterize a set of data...is to model the process that generated it." In view of the potential value of understanding the construct of control strategy, the decision was made to attempt to simulate the processes involved in continuous manual control behaviors, including the effects of control strategy.

The approach was to develop a computer simulation of the learning of continuous control behavior that embodied psychological constructs, and which could represent, through parametric manipulation, a variety of control strategies. The model was designed to reflect the organization, structures, and processes that are currently believed to be characteristic of human motor control learning and performance. This approach provides a precise, objective representation of control strategy, embedded in a psychologically plausible simulation. A major por-

tion of the research effort consisted of the design of preliminary tests of the validity of the simulation and its representation of control strategy. In testing, the control strategy employed in the simulation which best predicted human control output was used to make inferences about human control strategy. The initial validation procedures included comparing the characteristics of the inferred control strategies with those that would be expected on the basis of the original definitions of control strategy and examining the quality of the match between model predictions and human behaviors. If the inferred human control strategy varied in a sensible way with reference to the testing conditions, then this would testify to the validity of the simulation and its representation and measurement of control strategy.

The validation of the approach used here obviously involves complex questions of both construct and predictive validity. A construct, as Cronbach & Meehl (1955) have pointed out, cannot be validated by any single test, but rather must be empirically validated through a variety of tests in the situations in which the construct is believed to be influential. Predictive validity is important to this research because its ultimate goal is to permit the prediction of the effects of various cue configurations in training on strategy and performance in work settings. That is, the simulation would be used to measure developing control strategies during training, so as to tailor training conditions to result in optimal control strategies--effective not only in training but in on-the-job performance. This precise predictive ability can only be achieved by a thorough understanding of the construct control strategy. Thus the validation procedures have included first attempts at both types of validity.

The initial testing procedures used to validate the approach involved a simplified stimulus environment in a laboratory situation. Even though the ultimate utility of the simulation should be in a complex flight training environment, the simplified setting was selected due to the complexity of the problem being examined, and due to the difficulty of defining and measuring a mental construct such as control strategy. The simplicity of the test setting is not, therefore, an indication of long-term goals for application of this approach but rather is a reflection of the difficulty of the inference problems involved.

E. Summary

Flight simulation research should include identification of the necessary and sufficient cues to be provided in simulators used in flight training. High quality measures of the effects of cues on learning are needed to determine the most cost-effective ways to design and use simulators. Traditional measures of progress of training -- the various time and accuracy measures -- have weaknesses which make them inadequate as the sole representatives of the effects on training of various cues and cueing techniques. These measures are also of limited usefulness for making critical, fine distinctions between individuals at different

skill levels, or for predicting the transferability of training to real flight conditions. The present investigation addressed the problem of developing a measure of continuous manual control learning which could strongly supplement the information provided by traditional performance measures.

The approach taken was to try to measure the changing control strategies developed by people in the course of training. Strategies are viewed as parameters which determine how the information in the environment is used to make decisions about manual control actions. Existing mathematical modeling approaches for the measurement of strategy were considered but were rejected. Instead, we developed a psychologically based computer simulation of human operator learning in a preview tracking task. The simulation was designed so that it could represent a variety of control strategies which might be important to tracking performance. The simulation could predict a variety of patterns of control behavior, depending on the control strategy specified for it. Inferences about the control strategy used by an individual were made by determining the control strategy used by the simulation which best predicted human control behavior. Preliminary validation efforts included examining the quality of the simulation's predictions of human behavior and comparing the characteristics of the inferred control strategies with the characteristics control strategy is believed to have.

SECTION III

A THEORY OF CONTINUOUS MANUAL CONTROL LEARNING AND PERFORMANCE

A. Introduction

This section presents a theory of how high-level mental processes, parameters, and memory structures influence learning and performance in continuous manual control tasks. The mental processes to be discussed include both decision-making and automatic processes. The parameters define what will be called control strategy. The memory structures are organizations of task-related information in human long-term memory. These three aspects of continuous manual control learning will be described in detail and then unified in a summary discussion of their implications.

The theory was developed to provide an explicit basis for computer modeling of human learning and behavior in a manual control task. The computer program was designed to be used as a new, sensitive method for measurement of learning and performance in continuous manual control tasks. The ideas presented here also provide a basis for a unified program of training research independent of the success or failure of the computer program developed on the basis of these ideas. The theory provides a basis for research because of its detailed nature. That is, in order for the theory to be explicit enough for testing via a computer program, positions on several controversial issues were taken by the research team. The necessity for such definition has pinpointed a number of areas where additional research is much needed.

For the remainder of the section, the word task is defined as the collection of control behaviors used to achieve a specified goal. For example, one of the tasks of a pilot might be flying straight and level. Another task might be landing the aircraft in clear weather. Each of these tasks, defined in terms of the specified goals of "straight and level flying," or of "non-destructive landing," includes several subtasks. Controlling the pitch of the aircraft, for example, is a subtask in flying straight and level. Controlling the yaw and roll of the aircraft are also subtasks of the overall task of flying straight and level. Controlling velocity is still another subtask. This latter subtask is highly correlated with control of pitch, yaw and roll, in that control of pitch, yaw and roll manipulate the surface area of the aircraft relative to the airstream, resulting in changes in velocity. Part of the overall task of flying straight and level will be maintaining velocity in the face of changes in other subtasks caused by varying environmental demands. Because of interdependencies like this one, all the control behaviors (i.e., subtasks) involved in flying straight and level are considered to make up one task.

B. Mental Processes Important to Continuous Manual Control Learning and Performance

1. Decision-making Processes and Attention

Two categories of mental processes are very important to manual control learning: decision-making and automatic processes. Decision-making processes are defined in the following way. A decision-making process is a series of operations leading to a conclusion or to a report of a conclusion. A conclusion is a reasoned judgement or the necessary consequence of two or more propositions taken as premises.

Considerable psychological research has been directed to examination of the issue of which mental processes demand attention or a large portion of limited mental processing capacity (Kahnemann, 1973; Kerr, 1973; Posner & Boies, 1971). This limited processing capacity or attention is assumed to be distributed across a variety of attention-demanding processing activities. The types of processes normally considered to demand attention or to occupy most of the human limited processing resources (Kerr, 1973) are similar to those that are described here as decision-making processes. Attention-demanding processes are frequently assumed to operate serially, although alternatives (e.g., parallel processing) have not been experimentally ruled out. Decision-making processes, as the term is used here, are assumed to operate serially.

The specific decision-making processes believed important in continuous manual control learning and performance include:

1. Performance evaluation -- The process of performance evaluation involves comparison of desired or expected results with results actually achieved. The comparison is according to some standard or limit and is followed by one action or another, depending on the results of the comparison. Desired results might include system output, e.g., a cursor positioned in relation to a target. The comparison would be between cursor and target, according to an error criterion. In this case, performance evaluation involves monitoring for error. Performance evaluation may also include comparing the expected and experienced sensory consequences of an executed movement. Both Adams (1971) and Schmidt (1975) suggest that such comparisons are very important in motor learning. In this latter case, performance evaluation involves behavior monitoring. In any case, this type of comparison requires attention.

2. Association and storage of new task information in memory --Association and storage of new information in memory involves selection of cues for storage and the organization of information around those cues. In the verbal memory literature these processes are described as attention-demanding and involve considerable decision-making. Within the present theoretical context, however, the selection of cues for memory

of manual control tasks is believed to be an aspect of control strategy which modulates the association-storage process. It is not clear whether organization-storage takes attention in the context of manual control learning. However, since this is a controversial issue, it will be assumed that the association-storage process does take attention and is a decision-making process.

3. Developing responses to novel situations -- When the human operator confronts a situation in which the demands are new, choices about the course of action most likely to be successful must be made. Alternatives must be weighed relative to the task goal, and relative to their probable success. These choices involve considerable decision-making and take attention.

4. Developing responses in conditions of excessive error-- The human operator evaluates performance in the task and in subtasks according to a set of internalized standards. When that evaluation results in a conclusion that error is excessive, measures are taken to bring performance within acceptable limits. Such efforts require choices among alternative actions under the time pressure caused by perception of excessive error.

5. Determining when attention may be redirected to another set of decision-making processes -- The term set is used here in order to emphasize the idea that each subtask within a task is performed through the application of one or more of the decision-making processes discussed here. In some sense, the set of decision-making processes relevant to a particular subtask can be said to distinguish that subtask from others. The same decision-making processes may be active in two subtasks but are likely to be active in different ways due to differences in process inputs and outputs. For example, the task information appropriate to controlling altitude in an aircraft is distinct from the task information appropriate to controlling pitch in the aircraft. As performance in a given subtask improves, a decision may be made to continue devoting attention to this subtask or to devote attention to the processes associated with other subtasks. This determination is made in light of current task demands and performance levels as well as in light of other demands on the operator and involves decision-making.

6. Developing a more effective strategy for control -- The operator must apply the processes just described in performance of the several subtasks which constitute the task at hand. The style or strategy of application will be quite important to the overall effectivenessof the task. A concept of con-

siderable importance to the research reported here and to be described in some detail is that of control strategy. It is assumed that the process of developing a more effective control strategy is a process involving a multitude of decisions based on a variety of inputs and takes attention.

2. Automatic Processes

A second class of processes important to continuous manual control learning and performance are automatic or non-decision making processes. Automatic processes are of the sort that the literature has suggested take little or no attention (Kerr, 1973). It is not necessary for automatic processes to be performed one at a time. Unlike decision-making processes, automatic processes are likely to be performed in parallel with each other and with decision-making processes.

Automatic processes of special importance to continuous manual control learning and performance include the following:

1. Perception -- This process involves detecting a preselected subset of information present in the environment. Such selective perception occurs with well-learned or especially significant stimuli almost in spite of human intention (LaBerge, 1973). The effort required is believed to be small relative to that required by the decision-making processes described earlier.

2. Selection of well-learned motor commands -- This process involves locating in long term memory a motor command appropriate to a familiar environmental state.

3. Maintaining selected motor commands in short-term store --This process involves maintenance in memory for a period of a few seconds of a string of commands. It is assumed here that the selection or development of commands can occur more rapidly than does the execution of motor commands. This assumption implies the existence of such a process.

4. Execution of motor commands -- This process involves the execution of already-selected motor commands, and occurs automatically.

C. Parameters Important in Continuous Manual Control Learning and Performance: Control Strategy

1. Control Strategy Defined

The concept of control strategy is the central theme in this research. Control strategy is the object of measurement by the simulation described in Section IV. The methods used for application of the simulation to measurement are detailed in Section V. Control strategy is believed

to determine or define the functioning of the processes described previously. Through that determination control strategy profoundly affects the style and quality of human performance.

A parameter is a variable whose value determines the characteristics or behavior of a process. Control strategy is defined as the set of parameter values that determine the functioning of the processes important in continuous manual control. There are three categories of control strategy parameters. These three categories are:

1. Criteria for performance in all aspects of each subtask.

2. Stimulus cues on which to base performance.

3. Sequence for decision-making processes.

Each of these types of parameters influences the mental processes important in continuous manual control learning and performance in distinct ways. Criteria for performance provide a basis for a variety of comparisons important to motor skill learning. These criteria dictate, for example, standards for acceptable operator behaviors (e.g., timing, boldness) as well as standards for the controlled system's outputs (e.g., allowable error). Selection of stimulus cues determines which information the operator will perceive and will use as a basis for motor performance and for memory storage of newly experienced motor commands. The sequence for decision-making processes determines the order in which these processes may occur. Further discussion will clarify the various aspects of control strategy and the processes it affects.

As is apparent from the definition, choice of a control strategy does not include choices of mental processes although it does influence them. Other definitions of strategy, especially in the verbal learning and memory literature, have defined strategy selection to be a selection among mental processes for learning or performance. Omitting process choice from strategy selection might be criticized on the grounds that only a choice among processes could fully account for the flexibility and variability in human behavior. However, the present conceptualization does allow quite a large degree of behavior variability. Even though there is no variation in the mental processes involved, variation in control strategy produces considerable behavior variability and flexibility. For example, the parameter value set which specifies the stimulus cues on which performance is based can result in a memory structured about position cues in the environment. Given another parameter sec (i.e., a different strategy), the memory which develops may be based upon rate of change in the presented track or task goal. The behavioral consequences of these two strategies are quite different.

Another example of the behavior variability possible through variation of parameters controlling fundamentally constant processes is related to the sequence among decision-making processes. One individual

may devote considerable time to performance monitoring and very little time to remembering the cues in the environment in relation to his own actions. Such a strategy will result in quite different learning from a strategy in which explicit effort is devoted to learning cause and effect relationships in the task with very little attention to evaluation of performance early in learning.

2. Control Strategy Related to Mental Processing

Table 1 relates control strategy to the decision-making and automatic processes discussed previously. A defined task and a motivated operator are assumed. The construct of control strategy will be discussed in its relation to each of the processes.

Control strategy includes a parameter value set that defines acceptable performance or behavior in several aspects of the task. In Figure 1, two aspects are indicated: control output and control input. Control output is output from the system being controlled. Control input is control behavior on the part of the human operator. It is assumed that there exist criteria which determine acceptable ranges of control output. Such criteria might be in terms of the allowable differences between actual position compared to desired position. In a similar fashion, the energy or velocity with which an operator manipulates a task controller is likely to be limited by a control input criterion. This criterion probably varies among operators. Another limit related to control input such as stick motion has to do with the number of planned motions which must be stored in short-term memory before the operator is willing to devote attention to another subtask. Some operators may switch attention often, others may require a greater backlog of future plans before switching. Thus, one aspect of control strategy is the parameter value set that defines these behavior and performance criteria or limits. As shown in Table 1, these criteria affect performance evaluation and behavior evaluation. Control strategy criteria affect the set of commands from which responses to new or errorful situations are selected. They also provide a criterion for the switching of attention to another subtask, in that the operator will not switch unless a sufficient backlog of commands has accumulated in short-term store. Further, excessive error conditions are explicitly defined by criteria on control output. Finally, the entire parameter value set defines the dimensions of the overall goal of performance in the task, and this overall goal and the degree to which the operator is attaining it will influence the control strategy development process itself. Further development of control strategy is stimulated when overall performance is unacceptable, with reference to the task goal.

The second category of control strategy parameters determines the subset of environmental cues available as a basis for control. As indicated in Table 1, this parameter set affects several processes important in continuous motor control. For example, the stimulus cues used affect the performance evaluation process in the sense that they define what is used by the operator as a basis for comparison. The stimulus cues

TABLE 1

CONTROL STRATEGY INFLUENCE ON MENTAL PROCESSES IMPORTANT IN CONTINUOUS MANUAL CONTROL LEARNING AND PERFORMANCE

PROCESSES IMPORTANT IN CONTINUOUS MOTOR CONTROL	CATEGORIES OF CONTROL STRATEGY PARAMETERS: Criteria for Performance			
	Standards for System Output	Standards for Control Inputs	Stimulus Cues On Which to Base Performance	Sequencing Among Serial Processes
Performance Evaluation	Sets quality standards	Sets quality standards	Limits cues used	Specifies order
Association and Storage of New Task Information			Controls the information stored	Specifies order
Developing Responses to New Situations	Limits set of commands considered			Specifies order
Perception: Visual			Limits cues detected	
Perception: Auditory			Limits cues detected	
Perception: Proprioceptive			Limits cues detected	
Developing Responses in Conditions of Excessive Error		Defines applicable set of commands		Specifies order
Attention Switching		Limits when		Specifies order
Selection of Well-Learned Motor Commands				
Maintaining Responses in Short Term Store	Determines when a plan for action must be revised			
Execution of Selected Commands				
Control Strategy Development	Controls when need for modification of control strategy is signalled		Limits cues used	Specifies order

used define what information about the task actually gets organized into memory. Control strategy determines which sensory modalities are effective in the task and within a modality it determines which cues are actually used. For example, in the auditory modality, the operator might detect changes of frequency or changes in pitch. Control strategy also determines which stimulus cues are most likely to be detected by the control strategy development process.

A third category of control strategy parameters determines the sequence of decision-making processes. This sequence specifies the allocation of attention both across and within subtasks. The sequencing strategy includes specification of when or if the control strategy development process itself takes place. (Consideration of what this latter process may involve is postponed until the last part of this section.)

D. Structures Important in Continuous Manual Control Learning and Performance -- Internal Models

There are three different ways in which information important to continuous manual control tasks is organized in memory. These three memory organizations are termed internal models because they are mental models of the temporal relationships among important task-related events. The nature of these relationships is discussed below.

1. Task Controller Model

One of the ways of organizing task-related information is to relate states of the controlled-element to states of the control input. The controlled element may be a vehicle, a cursor on a video screen, or a tennis ball. The control input may be a steering wheel, control stick, or a tennis racket. The task controller model consists of learned associations between initial state of the controlled element, the state of the control input and the final state of the controlled element. The term state is used to imply the assumption that different sensory modalities and different cues within a modality may combine to provide a unitized basis for response selection. Separate aspects of the task controller (such as position, velocity or acceleration) are used together to achieve a desired state (or set of aspects) of the controlled-element. The functional aspects of these perceived states may include multiple cues from multiple modalities for one task and may also include aspects of other simultaneously performed tasks. The stimulus cue set used is specified by control strategy.

The nature of the state used as basis for response selection can strongly affect the manner in which a task is accomplished. Jordan (1972) provides evidence for the differences in performance which result from differences in the perceived state. Subjects were given visual cues, visual plus proprioceptive cues, or proprioceptive cues alone as a signal for a fencing move -- the disengage and lunge. Subjects given proprioceptive cues alone showed significantly faster reaction times than subjects in either of the other conditions. The study also

suggested that visual cues tend to dominate, even when they are not the best cues to use. The implication of this study is that selective emphasis on effective cue states during training can mean improved performance.

The idea of an internal task controller model is suggested by the literature on motor skill learning. Kelley (1967) argued for the existence of such an internal model of the task controller. Attneave (1974) proposed the existence of memory for associations among actions and their consequences. Schmidt (1975) described a recall schema: a rule abstracted from many instances of associating information about initial conditions, response specifications, and consequences. The schema was proposed as a way to account for human ability to perform in novel situations. This theory accounts for this ability to perform well in novel situations which results from orderly generalization in long term motor memory from experienced instances (of initial state, action, consequent state) to related instances which have not been experienced.

The idea of an internal model of the task controller also contrasts with motor program notions of memory for motor skills. Keele (1968) defined the motor program as a sequence of stored commands that is structured before movement begins, and which is carried out in its entirety uninfluenced by peripheral feedback. Most discussions of the motor program imply that this sequence of commands is stored together in long term memory. An internal model accounts for such automaticity, if the assumption is made that command execution takes longer than command selection. The command sequence is generated rapidly, stored as a sequence in short term memory, and then executed as a stream of control actions.

2. Input model

A second way in which information in memory is organized is one which permits prediction of upcoming input states, where the input state is defined as the desired state of the controlled-element. For a pursuit tracking task, the form of information which makes up the input model is quite analogous to that for the task controller model and for the neuro-muscular model. Here, the desired states of the controlled-element at previous instants in time are associated with the desired state at successive instants. In preview tracking, the displayed track is a temporal sequence of input states. In the absence of input preview, people use a predictive model of the input states to permit the structuring of movements and the monitoring of the correctness of self-initiated movements. A remembered song melody is an example of an input model which guides singing. The following discussion describes the evidence suggested this idea.

Evidence for the existence of such input predictive abilities, and hence, an input model, is rather strong. Many studies have shown that in pursuit and compensatory tracking, subjects learn to use the predictability in the input to improve performance. An especially inter

esting study is by Pew (1974a). Subjects were given a pseudo-random waveform to track in the pursuit mode over a series of trials. Unknown to the subjects, one portion of the track was repeated. Subjects improved on all portions of the track, but improved significantly more on the repeated portion than on the other portions, presumably because of its predictability.

Another supportive study was by Keele (1975). Subjects were trained to give discrete responses to a presented series of lights, given in a predictable order. If subjects were then presented the predictable light sequence, with one light out of order, reaction times to that light and those following it were slowed. This effect could occur because the out-of-sequence light violated the predictions of the input model.

Jagacinski, Burke, and Miller (1976) trained subjects to control a series of visually displayed oscillations of varying arc sizes, and then tested to see if what subjects had learned transferred to a speeded version. Large positive transfer effects did occur, and the authors suggested that subjects had learned state-to-state relationships of the input, as would be the content of an input model.

The existence of an input model allows not only structuring of movements in the absence of input preview (as in pursuit tracking), but also accounts for skilled self-monitoring of performance when no external standard is present. This idea is supported by major theories of motor skill learning which posit some form of input (afferent) model, which is used to monitor performance when an external standard is not available. Adams (1971) argues for the existence of a 'perceptual trace,' a form of motor recognition memory used to monitor correctness of an ongoing movement. The 'perceptual trace' is a record of sensory consequences of carrying out a correct movement. In the present theory, input defines the desired state of the task controller, which is partially described by the afferent feedback to be received from a correct movement. Memory for the desired state(s) of the input constitutes the input model. Thus, the input model for monitoring performance in the absence of an external standard is comparable to the Adams (1971) perceptual trace function and also to the function of the recognition schema proposed by Schmidt (1975). Pew (1974) recognized the abilities of humans to predict not only characteristics of an input waveform (his second level of motor performance functioning), but also to generate and monitor the desired performance sequences independently (the third level in his proposed hierarchy of motor skills). The input model accounts for both of these abilities.

3. Neuromuscular Model

A third way that task-relevant information is organized is as associations between central nervous system states and limb states. This is a memory representation of the neuro-muscular dynamics of the body, and is organized like the internal model of the task controller.

For most adults, the neuromuscular model is well-developed, as can be realized when injury or fatigue results in sudden distortion of the relationships stored in the model. A move which is normally easily accomplished is attempted, but due to injury or fatigue, the efferent signal issued is followed by unpredicted results, and the individual feels a sense of surprise. Pew (1974a) a reports an experiment in which he interfered with the neuromuscular model by effectively reducing the mass of a subject's arm. He subsequently observed behavior appropriate to the normal arm mass, which produced severe overshooting in the experimental task. Subjects reacted as if on the basis of a (temporarily) inappropriate neuromuscular model.

E. Theory and Hypotheses

1. Two Major Aspects of Control Task Learning

The three sets of assumptions about processes, parameters and structures important in human manual control learning and performance result in the following account of the course of events in motor control learning. Figure 1 displays the information flows and control relationships believed to most heavily influence continuous manual control learning. Learning of this type can be considered as involving two major aspects. The first of these is the development of the organizations in memory described previously. The task controller model and the input model and their relationships to the neuromuscular model determine the limits on how effectively the operator can perform the task. A second important aspect of task learning is the learning of an effective control strategy. How control strategy is learned is not a major focus of the research reported here. However, the effort to measure control strategy using a simulation has required the consideration of the characteristics of control strategy in enough detail to permit certain inferences about how it develops.

The following describes learning of internal models and control strategy, and their effects on performance. Model development is the first to be discussed.

2. Internal Model Learning

This part describes the way the processes discussed previously operate to form the internal models necessary for skilled performance. The individual begins learning a task with a control strategy that specifies the functioning of the task-related processes considered previously, i.e., performance evaluation, response to excessive error, storage of information in memory, attention switching, etc. The control strategy includes parameter values for the processes in all of the subtasks used, as well as for the sequencing among all processes involved in the task. These processes must occur in order for the task to be performed; some initial parameter values are used to prescribe their execution. The joint functioning of these task-related processes serves to develop the internal models important for the task.

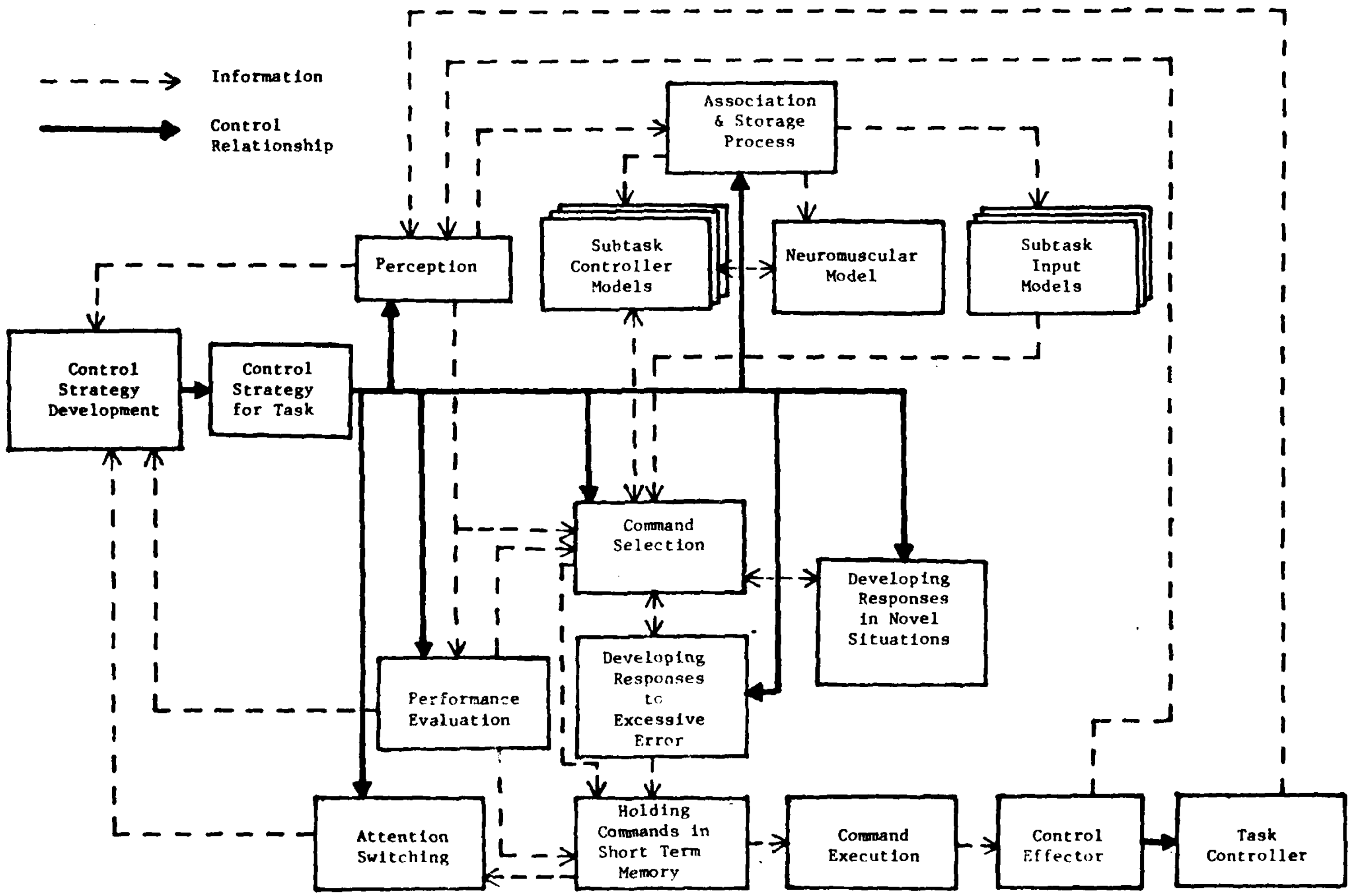


Figure 1. Relationships Among Control Strategy Parameters, Mental Processes, and Memory Structures in Continuous Manual Control Learning and Performance

For example, the association and storage process is directly involved in structuring the internal models described previously. The other processes can interact with its functioning and thus affect the speed of development of the memory organizations or even the content of these. If the operator devotes a great amount of attention to processes other than association and storage, development of memory will be slow. If the operator attends to a particular set of cues in the process of perception, the content of the memory will be different than if another set of cues had been attended to.

The balance between decision-making and automatic processes changes in the course of learning in order for the most effective development of internal models to take place. Early in learning the processes most frequently active are decision-making in nature. This stage is analogous to Adams' verbal-motor stage of task learning (Adams, 1971). During this stage the operator must associate and store in each of the subtask controller models the relations between output transitions and specified command inputs. As these models develop, the operator can begin to use them, in conjunction with the already existing neuromuscular model, to exert effective control. For example, if the operator wishes to move a cursor visible on a screen from one position to another, the task controller model (memory) of the control stick-to-cursor dynamics can be accessed to provide the control stick motion necessary to accomplish this. The neuromuscular model provides the neural signals necessary to accomplish this motion at the correct time. As manual control skill develops, the operator takes into account not only his own neuromuscular dynamics (the control effector in Figure 1), but also the dynamics of the task controller.

In some tasks, for example those that are compensatory or pursuit in nature, the operator must develop an input model through the association and storage process. That is, present and immediately past desired states of the task (such as positions of the moving marker on a video screen) must be associated with desired future states of the task through observation of temporal relationships among these states. As input models develop, the operator gains the ability to anticipate upcoming demands in the task, and can prepare motor command strings on the basis of that anticipation.

Along with association and storage, performance evaluation occurs very frequently early in internal model learning. The operator must frequently compare the results of his control actions with the standard specified by the control strategy. The operation of this comparison process aids model development by triggering more or less drastic responses (depending on the operator's control strategy) to the error that inevitably occurs early in learning. Such responses along with their effects, are used as data in the models.

Performance monitoring and evaluation not only involves comparison of system output states with those desired, but may also, in some tasks,

involve comparison of the effect of the motor command executed (e.g., limb and control stick position) with the intended effect of the motor command. That is, early in learning, the operator may need to 'calibrate' his control input response to account for the 'feel' of various stick types. A third comparison that may be involved in the performance evaluation process is the comparison between experienced proprioceptive feedback with proprioceptive feedback that had been expected (specified by input models). These comparisons, too, would be defined by control strategy. Such comparisons with input models, however, cannot occur effectively early in learning because the necessary input model has not yet developed.

Another process which operates to store information in the internal models required for skilled performance is the development of responses to new situations. Early in learning the operator frequently encounters novel situations--situations for which no memory exists as to the effective action to be taken. The operator must develop these responses and this development results in the execution of trial commands. Their results are remembered (stored in the model) and used later. The set of commands considered acceptable is defined by control strategy.

All of these activities occur more frequently early in learning than later for the internal models to develop. The result of this occupation of operator capacity with these decision-making processes is that the operator has little or no spare capacity for other tasks. Indeed, the operator may be hard-pressed to perform even the subtasks necessary for task performance early in learning. Later in the learning process, the decision-making processes discussed here are needed less often. The operator normally is required to respond only to situations for which he has developed responses which can be selected and executed with little or no attention. Excessive error seldom occurs and attention is not required for error correction. Such reduction in processing capacity requirements that may occur after the internal models become well-established permits the operator freedom to devote his capacity to other sorts of mental processing, to other tasks or to the development of an improved control strategy for the task at hand.

3. Control Strategy Development Aspect of Task Learning

A second important part of task learning is control strategy development itself. The development of control strategy is a process that has seldom been considered in the psychological literature. The definition and assumptions about control strategy developed in this research have permitted some consideration of this apparently quite important development process.

Control strategy development is believed to involve the learning of certain relationships among the outputs from performance evaluation processes and the outputs from perceptions in the various subtasks. The significant relationships include correlations between perceptual cues and task performance, as well as correlations between the various perceptual cues.

The discovery by the operator of both these classes of relationships is important in two ways. Discovered relationships between performance or behavior evaluations and the perceptual cues used provide the guidance for reselection of cues that are used, i.e., the available cues acquire meaning in terms of the task goal. A second way in which these correlations, when discovered, are valuable to the operator results from the fact that in many tasks, the subtasks themselves are closely related. The discovery of these relations may permit the operator to use cues common to different subtasks and thus reduce the number of cues attended to. This reduces the complexity of the control that must be exerted. For example, an increase in pitch in an aircraft will result, in the absence of further action, in a decrease of velocity and/or altitude. When the operator learns this relation, those three subtasks may be combined in the sense that control strategy can specify common cues on which to base response. The result will be the smooth adaptation of those control aspects to task demands and increased ability of the operator to perform other tasks. The latter is true since the number of mental processes devoted to the task is now reduced by the number of subtasks which were unitized.

A second major point about the course of control strategy development is that in the absence of explicit attention devoted to training control strategy, there are likely to be wide individual differences in the control strategies used. These differences will be especially apparent early in learning. This is because the initial control strategy used by an individual is largely a function of the past task history of the individual. Generalization from past experiences leads the individual to use a control strategy or elements of control strategies used in tasks similar to the task to be learned. If individuals come to new tasks with different task histories, the control strategies initially used will vary widely between individuals. This variation might be indicated by the lack of a systematic differences in the control strategies used in different training conditions early in learning. (This hypothesis was tested in the experiment described in Section V.)

Individual differences in control strategies used will also appear later in learning. Sources of these are the differences that exist in individuals' willingness or ability to devote attention to the development of an effective control strategy. Furthermore, individuals are likely to differ somewhat in their perceptions of task demands and of the significant task characteristics.

The above discussion implies that control strategy is diverse and plastic. If this is so, it suggests that control strategy can be directly shaped by the training conditions provided. (This hypothesis was also initially tested in the experiment described in Section V.) If training conditions affect control strategy, and if explicit attention is given to the training of control strategy, then control strategy can be molded into preferred forms. The preferred, or optimal, form for control strategy in a task might be one which is associated

with relatively high quality performance and low mental effort in the task compared to other control strategies. Such a high performance, low effort strategy would provide the operator with excellent ability to respond in 'high-load' situations -- danger, or the sudden addition of another task.

Optimal strategies may or may not be spontaneously developed during training. Three factors are responsible for this: the existence of wide individual differences in control strategy, the fact that current training practices do not include training for strategy, and the fact that physical differences exist between training situations (such as simulators) and actual task environments (such as aircraft). This latter factor seems to be important because some strategies which permit low error in training may not be optimal for the actual task itself. For example, trainees may base their control strategy at least in part on task demands and characteristics unique to the training setting.

4. Control Strategy and Improved Measurement Systems

These ideas about the importance of control strategy and its susceptibility to training influence, when considered together with the specific aim of this research -- the measurement of control strategy -- suggest a new approach to the design of training for continuous manual control tasks. The first step in the approach would be to identify the optimal control strategy for a given task. Considerable effort would be involved in this step since the control strategy for a single task includes a variety of parameter values - those specifying criteria on performance, stimulus cues used, and the sequence of decision-making tasks. Measurement of these parameter values could be accomplished by means of conventional empirical methods or by means of an extension of the simulation developed in this research.

The effort expended to identify optimal strategies for tasks should be well worthwhile for two primary reasons, both of which have direct implications for design of training programs.

The first reason is that when the control strategy optimal for a task is defined and identified, better training programs can be developed. Training can be aimed at training optimal control strategies as well as at prompting the development of the internal models described previously.

A second reason for defining and identifying the control strategy optimal for a given task is that these efforts will make possible much more accurate prediction of trainee performance. Such predictions will be possible because measurement of control strategy can provide a much-needed supplement to conventional performance measures. Identification of the control strategies used by individuals during training can be used to describe differences in their performance that may not be apparent from conventional performance measures. Transfer of training to the actual task setting can be predicted on the basis of the simil-

arity in the trainee's control strategy to that most effective for the actual task. Transfer of training to other tasks can also be predicted by examining the similarities in the trained control strategy and that appropriate for a different task. The effects of cues which might be used in simulators or other training settings can be predicted by measuring the cue utilization aspect of control strategy. This could be accomplished by examining the effects of particular training cues on the control strategies of trained individuals already using an optimal control strategy. Cues which do not change the control strategy when removed are irrelevant and not necessary for training conditions. Cues which cause a shift away from the optimal control strategy when included, are distracting and should not be included in training. Cues which cause a shift in control strategy when removed and maintain the optimal control strategy when removed are necessary to include in training. The potential value of this approach for the design of cost-effective training means that control strategy measurement, by simulation or by other means, should be a major goal for research in experimental psychology.

This section has been devoted to a presentation of a theory of manual control learning and performance. The theory was developed as part of a particular approach to the goal of providing improved performance measurement -- measurement by simulation of an important aspect of performance, control strategy. The approach to measurement by using a simulation was initially tested in a laboratory setting in this research. The results, which are detailed in Section V, were quite encouraging. Even if the results had not been encouraging, or even if their extension to a more realistic setting proves infeasible, the theory is important. It can guide the development of a measurement system for continuous manual control tasks that is much more precise (hence, much more useful) than those which presently exist.

SECTION IV

HUMAN OPERATOR PERFORMANCE EMULATOR

A. Introduction

HOPE (Human Operator Performance Emulator) is a psychologically based computer simulation of continuous manual control, which includes a representation of control strategy. HOPE currently simulates tracking behavior based on use of visual information only. However, HOPE was developed from a broader theory of psychomotor behavior (see Section III) which applies to a wider range of behaviors and information processing activities. The HOPE simulation and its representation of control strategy are based on the psychological literature. The following discussion describes the relation of the simulation to that literature.

B. Psychological Constructs and Processes Embodied in HOPE

This part introduces HOPE in general terms for the purpose of describing how its structures and processes relate to current psychological representations of information processing and to the theory presented in Section III. HOPE is a hierarchical model in which there is a clear distinction made between two levels of processes. Although the psychological literature has variously labeled these levels as conscious-subconscious, attentive-preattentive (Neisser, 1967), controlled-automatic, most models of information processing recognize a distinction between processes which demand attention and must be performed one at a time and the processes which do not demand attention and can be carried out in parallel. In HOPE, one level of processing is represented by a Supervisory Processor that can perform a variety of operations but only in a serial fashion. The constraint that the Supervisory Processor can perform only one function at a time links HOPE with single-channel models of human information processing (Welford, 1952). In contrast, the second level of processing includes a number of lower-level subsidiary processors, each dedicated to a single process, but which can operate in parallel. These two levels of processes are represented in Figure 2, an information flow diagram of HOPE. In the discussion which follows, capital letters are used to distinguish processes that exist in the HOPE program. As indicated by the theory in Section III, the Command Selection Process and the Command Execution Process in HOPE are both subsidiary processes which can carry out their functions in parallel without interfering with one another. In contrast, processes such as Performance Monitoring or the Satisfactory Command Search cannot be carried out in parallel, since each fully occupies the Supervisory Processor when its functions occur.

Assignment of a process as a Supervisory Processor function or Subsidiary Process function coincides with descriptions of which mental operations make heavy processing demands on the human's limited processing capacity. Posner and others (Kahneman, 1973; Posner & Boies, 1971)

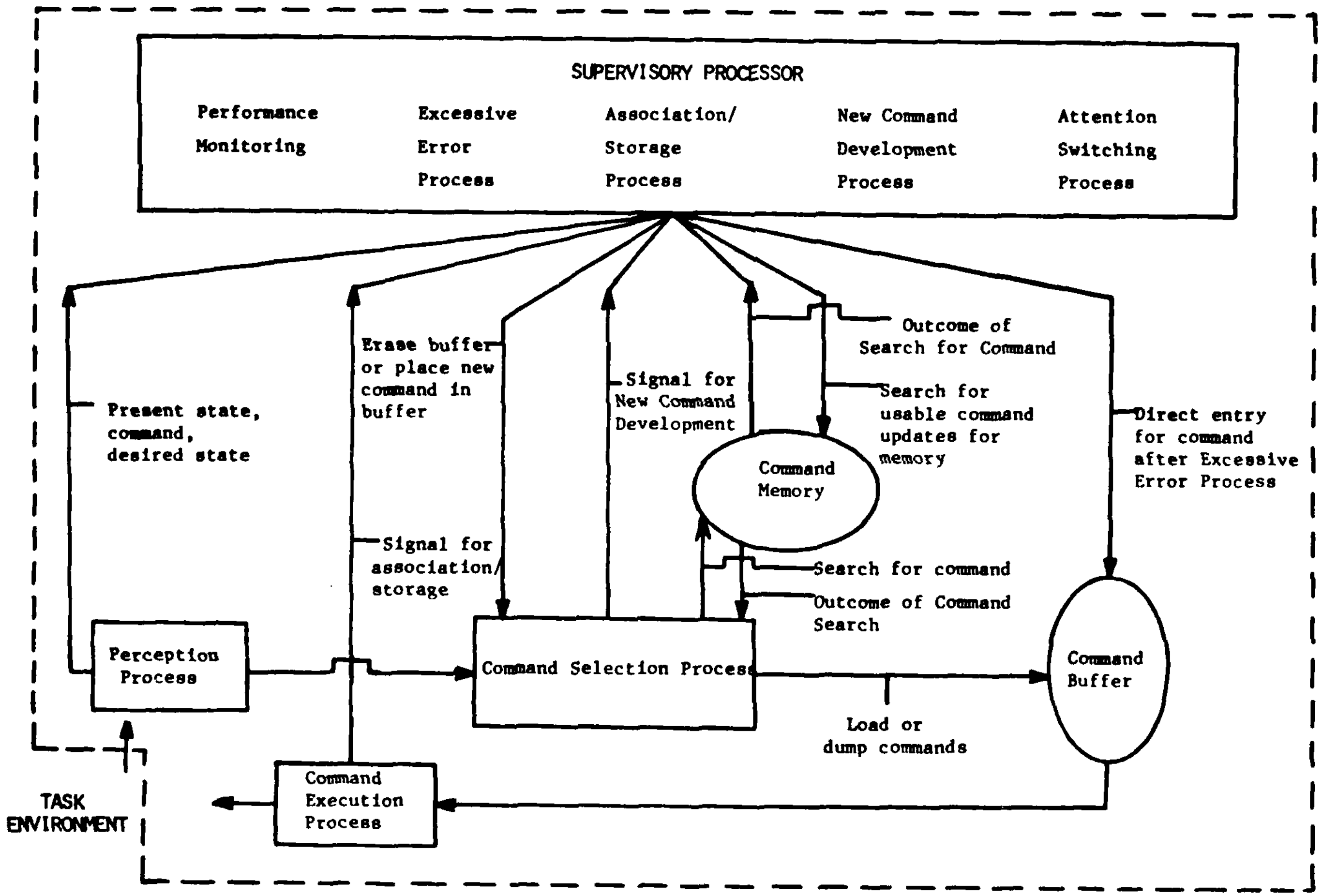


Figure 2. Human Performance Emulator (HOPE)

have suggested that human information processing is constrained by the human's limited processing capacity, which is taxed in varying amounts by different mental operations. Their research suggests that processes similar to the Command Selection Process which involve locating information already stored in memory do not make heavy demands on processing capacity and can be carried out in parallel with other processes, as occurs in HOPE. Executing already-selected motor commands (Command Execution) also makes a relatively low demand on processing capacity. In contrast, processes such as monitoring the outcome of fine motor movement (Performance Monitoring) or organizing information for memory storage (Stimulus-Response Association Process) make heavier demands on processing capacity. If these processes are performed together, they interfere with one another (Kerr, 1973); therefore, they tend to be performed in a serial fashion.

HOPE reflects the two-store theory of memory current in the psychological literature (Atkinson & Shiffrin, 1968; Broadbent, 1971). Two-store theories of memory suggest that the varying characteristics of memory are attributable to the retrieval of information from two different types of memory stores -- a long-term memory, which is of relatively large capacity, and a short-term memory, which is of relatively small capacity. The Command Memory (see Figure 7) is HOPE's long-term store for learned motor commands. It is organized in an associationist fashion whereby commands are located in memory at a point reflecting external states (i.e., cursor positions) that have preceded and followed a motor command. Although the content of motor memory is a topic of dispute (see Schmidt, 1975), HOPE's Command Memory organization is consistent with associationist views of long-term memory (Baddeley, 1976; Wickelgren, 1969).

The Command Selection Process retrieves commands from the Command Memory and loads them into the Command Buffer, HOPE's representation of short-term motor memory. The Command Memory is theoretically unlimited in size, whereas the Command Buffer stores only a limited number of commands for a short period of time. The Command Buffer stores the selected commands until they can be executed by the Command Execution Process, or until the Supervisory Processor directs those commands to be dumped.

The HOPE simulation addresses many of the criticisms aimed at mathematical models of control behavior (see Section IIC of this report). Its Perception Process allows information to be input only at discrete intervals, thus reflecting the human operator characteristic of intermittency. The execution of each command in HOPE is delayed until the previous command terminates, causing the model to exhibit behavior similar to that associated with the human psychological refractory period (Welford, 1968). The storage of commands in the Command Memory allows it to improve performance on the basis of previous experience, and thus, to "learn" over the course of performance. As discussed in Section III, the theory on which HOPE is based also includes a learned input

model which allows the simulation to use past experiences to make predictions about future performance demands. Further, HOPE is an emulation of individual behavior and thus can be used to measure the performance of individuals as well as group or crew performance where one individual's performance directly impacts that of another in a time-varying, multi-task environment.

Finally, HOPE is an imperfect performer, as, of course, are human beings. There are two major sources of error in the HOPE simulation. The first, if encountered in a human being, is what would be termed educated guessing. That is, until HOPE experiences a certain control task, its Command Memory for the task is empty, and certain simplifying default commands (educated guesses) are used. These are unlikely to produce the exact result desired; and although their effects will be stored at the proper location, these effects are likely to be in error in terms of what was intended.

A second type of HOPE error is caused by the limited capacity of its Supervisory Processor. Errors in timing occur when processes which must be executed by the Supervisory Processor must be delayed in a queue until the Supervisory Processor becomes available. Such errors cause some inaccurate information to be stored in the Command Memory, especially early in learning. Both of these types of errors become less frequent as HOPE becomes more experienced at a task. Thus, for the HOPE simulation, as for humans, practice is required for attainment of high quality performance.

In summary, HOPE mimics the psychological organization and processes which are believed to underlie human psychomotor behavior. Further evidence of this will be presented in the detailed discussion of HOPE's operation. It should be evident that the design of HOPE required considerable development of specific ideas about processes not explicitly described in the psychological literature. These ideas may be somewhat controversial, and are deserving of further study in themselves.

C. Control Strategy Representation in HOPE

In Section III, control strategy was defined as the outcome of a set of decisions determining an operator's distinct style of performance in manual control tasks. It is a parameter set that consists of:

1. Criteria for performance in various aspects of each subtask;

2. Stimulus cues on which performance is based;

3. A sequence for performance of decision-making processes.

It was suggested that control strategy should have the following characteristics:

1. It affects task performance.

2. The control strategy of an individual influences the course of training and thereby affects the learning of a task.

3. The type of control strategy used depends heavily on conditions experienced during task training and on prior experience with similar tasks and situations.

4. A task-specific control strategy is itself learned during training.

The definition of control strategy cited previously is represented in the HOPE simulation in terms of three variable control strategy parameters. The three parameters are:

Command Operative Time (COT) - the duration of a single motor command;

Error Limit (ERRLIM) - the amount of error allowed before major error corrective measures are initiated;

ADJUST - the magnitude of control response to excessive error.

These parameters are closely associated with the definition and characteristics of control strategy that have been described. All three parameters define criteria for behavior. COT sets a criterion on the duration of control movements and hence moderates the frequency with which a control stick can vary in position. ADJUST is also a criterion on control movements - it determines how boldly the control stick is moved in conditions of excessive error. In contrast, ERRLIM sets a criterion on the amount of error allowed in the controlled element's position, i.e., the extent of cursor position error allowed before major error correction occurs.

The representation of control strategy in HOPE currently does not allow variation in usage of environmental cues. This is because for the preliminary testing HOPE was designed to operate in a simplified stimulus environment, and therefore takes account of visual position information only. Further development of HOPE would allow it to process a variety of environmental cues, and would include control strategy parameters guiding the choice of cues. Neither is the sequence among decision-making processes permitted to vary. The task simulated involved no subtasks, and the sequence of processes within the task was fixed in the manner described in Section IV (D-1).

Finally, the application of the HOPE simulation to measurement embodies the ideas about the characteristics of human control strategy developed earlier. That is, inferences about an individual's control strategy are made by a procedure (see Section V) which occurs frequently

enough (every 20 sec) to permit comparison of estimated control strategy with the time-varying nature believed to characterize control strategy.

D. Operation of HOPE

HOPE is a computer simulation of one example of continuous control behavior -- one-dimensional preview tracking. The present HOPE operates on a numerical representation of visual information representing a track. Modulated by control strategy parameters, HOPE generates control stick positions related to performance of a preview tracking task in which the task is to maintain a cursor on a track by manipulating a control stick. Discussion of HOPE will begin with a description of the Supervisory Processor and how it allocates attention among its functions. Then, each of the subsidiary processes and the details of the functions performed by Supervisory Processor will be discussed, followed by a detailing of the functioning of fixed process parameters and of the variable control strategy parameters.

1. Allocation of Attention by the Supervisory Processor

As seen from Figure 2, there are five jobs to be performed by the Supervisory Processor. In terms of theory discussed in Section III, these jobs involve attention-demanding processes and include performance monitoring, intervening in the case of excessive error, storage of executed commands and their outcomes, determining satisfactory commands when the subsidiary processes are unable to do so, and determining when attention can be temporarily switched to another task.

One problem which had to be addressed was how the Supervisory Processor would allocate its attention among the demands of the five different processes it performed. The Supervisory Processor can perform only one function at a time, so there was a need to specify the order in which simultaneously requested functions would be carried out.

Three possible ways of handling the attention allocation problem were considered. The first, and most straightforward, was to put all requests for Supervisory Processor attention into a list or queue on a first-come, first-served basis. This method insures that all requestors will be answered when their request comes to the top of the list. However, it does not allow certain requests to have higher priority than other functions.

One method for prioritizing requests is a concept called polling. In this approach, the processor asks each of the potential requestors if its function needs to be performed. It polls each of the requestors in a sequence indicative of their respective priority. However, this method is intuitively unappealing because it seems inefficient for the multi-purpose Supervisory Processor to have to spend some of its time polling for processing requests.

A third method, which avoids the undesirable aspects of polling, is the interrupt method. In this method, each requestor demands the use of the processor whenever it is required. A priority scheme can be implemented within the processor such that any interrupt which occurs is considered in the face of any other interrupts present or against the priority of the task currently in execution. The interrupt method insures that the highest priority task is always the first one to be completed. However, this method has the disadvantage that lockouts may occur. A lockout is a condition in which some number of relatively high priority requestors constantly keep the Supervisory Processor busy serving their repeated requests so that lower priority tasks never obtain the services of the processor.

Each of these schemes has its advantages, disadvantages, and specific applications, but none of them individually were suitable or justifiable for HOPE. Therefore, in HOPE, a combination of the queuing process and the interrupt method was implemented to provide what seemed to be the necessary attention allocation function. The combination chosen was as follows. Requests for Stimulus-Response Association, Satisfactory Command Searches and Attention Reallocation are recorded in a queue. If several of these requests occur simultaneously, a loading priority scheme determines the order in which these requests are loaded into the queue. The highest priority function is the Satisfactory Command Search, with Stimulus-Response Association and Attention Reallocation following in that order. This order was chosen for two reasons. First, the order reflects the (hypothesized) frequency and importance of the function during learning, with more frequent and important functions having higher priority. The Satisfactory Command Search is very important early in learning when the Command Memory is relatively incomplete. Similarly, Stimulus-Response Association is important early in learning for commands to be stored in the Command Memory. Attention Reallocation is likely to disrupt performance at this time. The priority scheme is also dictated by real-time estimates of the execution time for each of these functions. The lowest priority functions are the ones believed to take the most time (see Section IV D-7). Thus, the implemented loading priority scheme for queuing allows the most important, but fastest, functions to be performed first. It should be noted, however, that because of the queue approach for handling these requests, they are all handled regardless of the loading priority scheme.

Requests for execution of the Excessive Error Process are handled on an interrupt basis. When this type of request occurs, this process is always the next to be executed. This is not to suggest that execution of this process begins immediately, for any on-going process is completed prior to initiation of the Excessive Error Process. It seems logical for the Excessive Error Process to interrupt other processes, for if it did not, performance would continue to deteriorate.

The last remaining task of the Supervisory Processor is Performance Monitoring. Performance is checked after completion of any of the other

Supervisory Processor functions. When the Performance Monitor determines that performance in unacceptable, it initiates the Excessive Error Process.

In summary, the Supervisory Processor handles its five functions, one at a time, on the basis of a combination of an interrupt and queue system. Figure 3 illustrates this overall scheme. The sources for requests for Supervisory Process functions will be presented in the following discussion of the subsidiary processes.

2. The Perception Process

The Perception Process acquires information necessary for task performance, and translates it into a form usable by other HOPE processes. In the present HOPE, the Perception Process provides to other processes information about the current desired state (i.e., the center of the track), the actual state (the current cursor position), and the current command. This process occurs periodically, producing shapshots of the task environment spaced in time by the duration of perception. It reflects a basic characteristic of the human operator - intermittency -the processing of information at discrete intervals (Bertelson, 1967).

The Perception Process makes its information available to the other HOPE processes. Each new perception replaces the previous, so that in terms of duration exceeding a perception, there is no perceptual memory. Figure 2 shows that the Perception Process does interact with the Supervisory Processor. This interaction, however, is not a request for service, but rather an information input for use by the Supervisory Processes. Figure 4 indicates the functioning of the Perception Process.

3. The Command Memory and Command Selection Process

The Command Selection Process and the Command Memory are responsible for locating and maintaining information which enables HOPE to track. The Command Memory stores information which describes the observed operating characteristics of the task controller. The task controller intervenes between a control input (such as a control stick position) and a controlled element (such as a cursor visible on a video screen). The Command Memory stores information about the task controller without the use of an algebraic characterization of the relationship between the control input and the controlled element. As previously discussed (see Section II), such algebraic representation would reduce the psychological validity of the model. The present approach provides a simulation of learning of the task controller, whatever its characteristics. The organization of HOPE's Command Memory allows control skills to develop beginning with HOPE's first encounter of a given task. Algebraic models require the specification of some canonical form of the task controller in order to function, and that departure from psychological validity is a primary reason for the choice of the present approach.

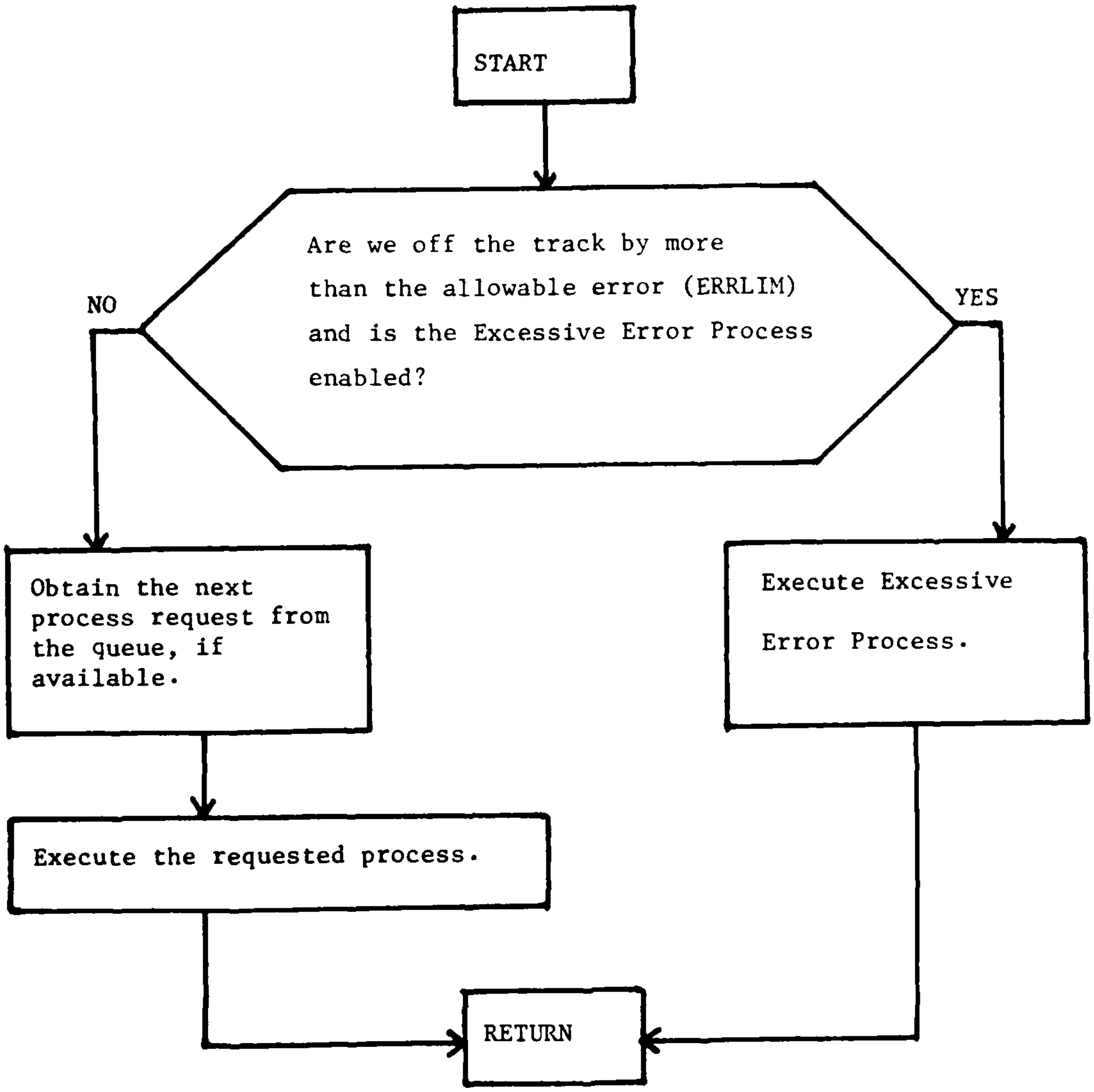


Figure 3. Supervisory Processor Resource Allocation Scheme

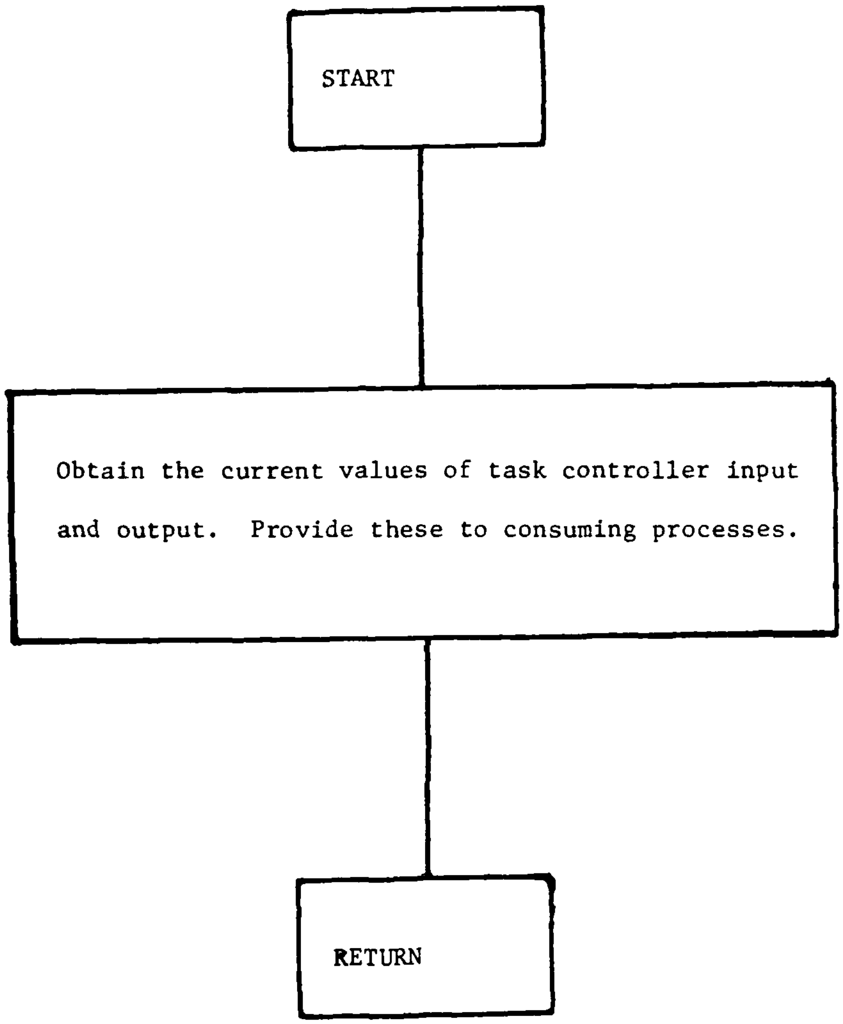


Figure 4. The Perception Process

The operating characteristics of the task controller are stored in the Command Memory of HOPE in terms of a set of commands which are learned only through experience. Information is stored in the Command Memory as follows. The task controller input (i.e., control stick position U) and output (i.e., controlled element, or cursor position X) are observed/recorded by HOPE at periodic intervals, producing a set of ordered pairs U_{ti}, X_{ti}, which are the values of controller input and controller output, respectively, at time t_i. These data are organized in an array, in which the rows are indexed by X_{ti}, the columns by X_{ti+1}, and the value at location X_{ti}, X_{ti+1} is U_{ti}. The array and its contents constitute the Command Memory. (The equivalence between this representation and a differential equation representation of the task controller is provided in Appendix A.)

With an array loaded in this fashion, the correct command input to the task controller for making an output change from one state at t_{i-1} to another specified state at t_i, can be determined by reading the needed command at the location pointed to by the states of interest. Furthermore, since the array is updated only by actual experience, then finding a command at the indicated location indicates that the state desired at t_i will occur if that command is used. Thus, the "predicted state" at t_i can be used in finding a command to get to the desired state at t_{i+1}. The state at t_{i-1} is referred to as the "last predicted state." (Note that, initially, the "last predicted state" is the present state.) The state at t_i is called the "desired state." The amount of time between t_i and t_{i-1} is variable, depending on the value specified for Command Operative Time (COT). Thus, the Command Memory for a HOPE model with a COT of 40 msec would develop differently from the Command Memory for a model with a COT of 200 msec.

The Command Selection Process performs the function of looking up commands in the Command Memory and updating state labels. The Command Selection Process addresses the Command Memory at the location pointed to by the desired state and last predicted state. The located command is sent to the Command Buffer, and the (predicted) desired state is used as the last predicted state. The next desired state from Perception Process becomes the desired state. Repeating the process incrementally builds a string of commands in the Command Buffer for sequential execution. The command string serves the functions of what has been referred to as a "motor program". However, it permits more flexibilty in response than does a pre-stored string.

The question naturally arises: What if the Command Selection Process finds no command at the location specified by the last predicted state and the desired state? When this situation occurs, the Command Selection Process generates a request to the Supervisory Processor to perform a Satisfactory Command Search. This function is one of the queued functions discussed previously. The actual process which occurs during the Satisfactory Command Search is described below in the detailed explanation of the functions performed by the Supervisor Processor.

As will be seen, the Supervisory Processor always produces a command for use in this situation and supplies it to the Command Selection Process for entry into the Command Buffer. The Command Selection Process is shown graphically in Figure 5.

4. The Command Buffer

The Command Buffer acts as a storehouse or backlog for the commands selected by the Command Selection Process for ultimate execution by the Command Execution Process. The Command Selection Process occurs much more rapidly than the Command Execution Process and, as a result, a backlog of commands is produced and stored in the Command Buffer. This backlog of commands functions as a motor program, a set of commands which can be run off in an open-loop fashion. Most discussions of motor programs imply that the command sequence is stored as a unit in long term motor memory (Keele, 1975). In HOPE, however, the sequence is not obtained in whole, but is built up step-by-step, one increment at a time, based on task requirements.

As seen from Figure 2, the Command Buffer not only interacts with the Command Selection Process and Command Execution Process, but also provides information on the current command backlog to the Supervisory Processor and can receive commands directly from the Supervisory Processor in certain situations. This command backlog will be important in the discussion of the Attention Reallocation Process. The source of the direct entry commands into the Command Buffer will be identified in the examination of the Excessive Error Process.

5. The Command Execution Process

The Command Execution Process might be envisioned as the neuromuscular transducer which provides the actual control inputs to the task controller based on commands obtained from the Command Buffer. This function is accomplished as follows. Each command is obtained from the Command Buffer and executed as constant command for a discrete but minute amount of time. Typically, a command would last for approximately 100 msec, although in HOPE this varies with one of the Control Strategy Parameters. When this period of time expires, the Command Execution Process requests the next command from the Command Buffer. If none is available, for whatever reason, the Command Execution Process merely repeats the execution of the last command it obtained from the Command Buffer until more commands become available from the Command Buffer. Each time a command is started, a signal is provided to the Supervisory Processor. This signal is interpreted by the Supervisory Processor as a request for Stimulus-Response Association and is loaded into the queue for processing in turn. Figure 6 depicts the Command Execution Process.

6. Functions of the Supervisory Processor

Previous sections have discussed HOPE's subsidiary processes, and have indicated the sources of requests for action by the Supervisory

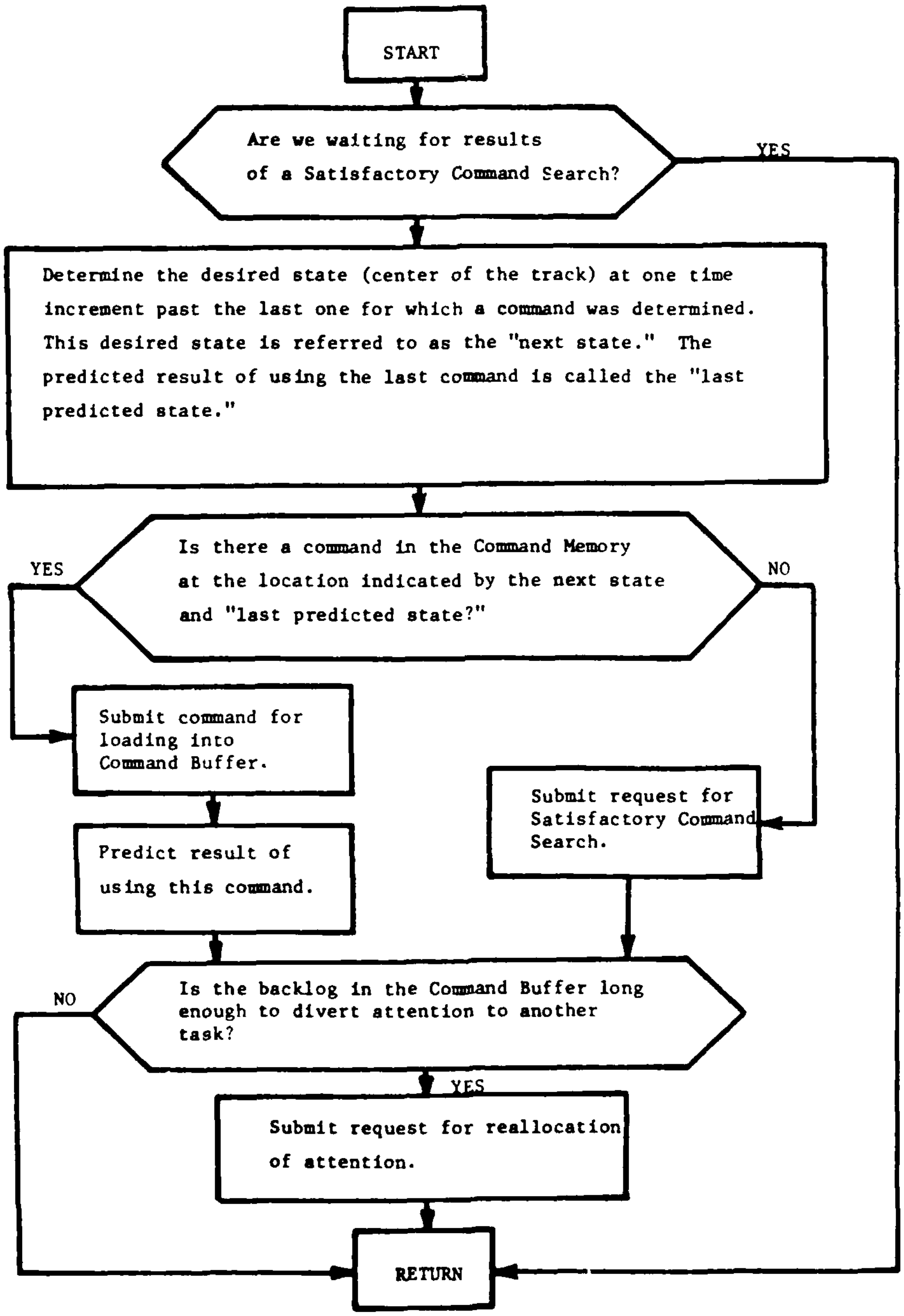


Figure 5. The Command Selection Process

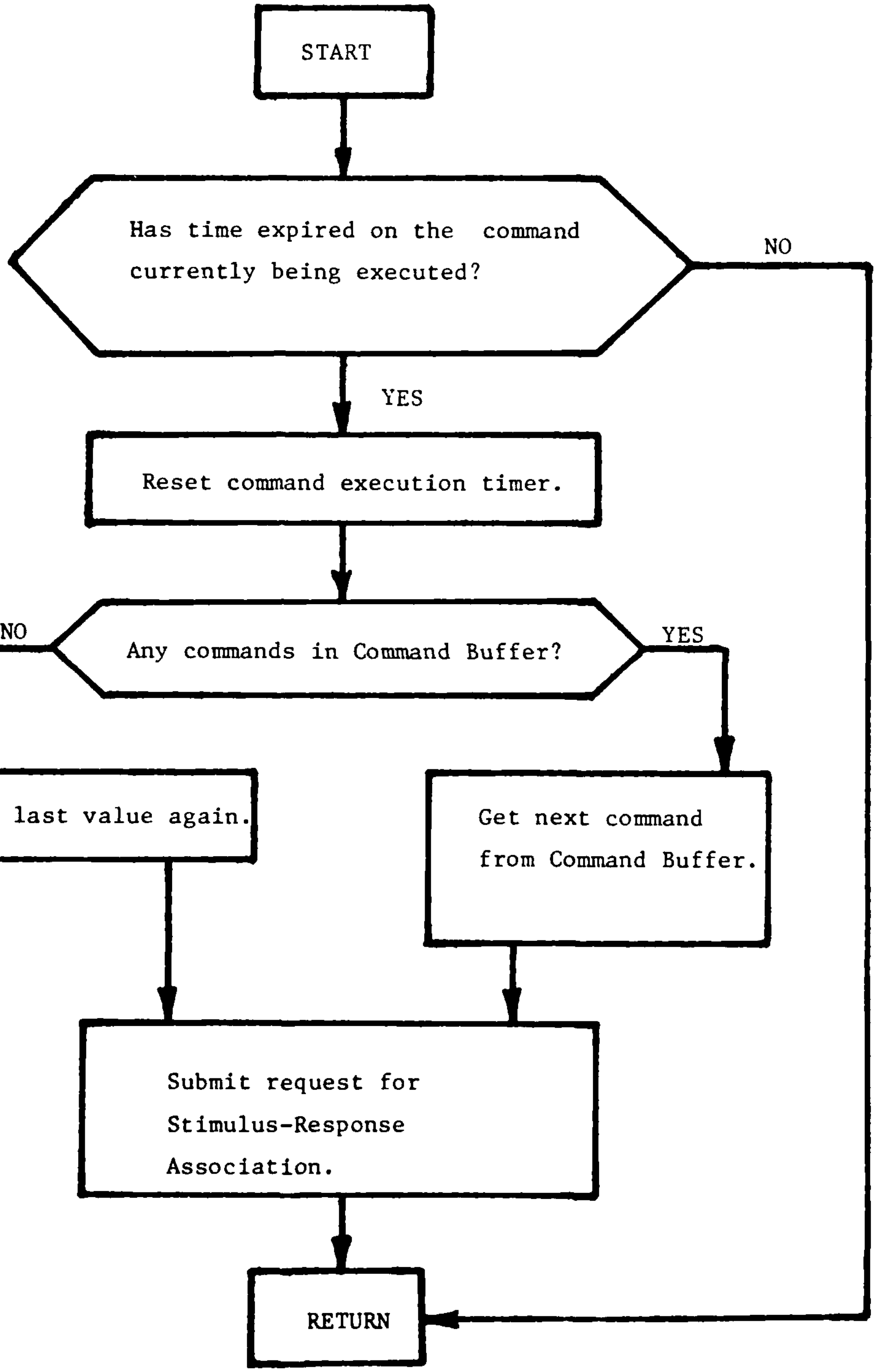


Figure 6. Command Execution Process

Processor. Table 2 summarizes the source of such requests and resulting response by the Supervisory Processor.

TABLE 2

SOURCES OF INPUTS AND FUNCTIONS OF THE SUPERVISORY PROCESSOR

Source	Input to SP	Desired Supervisory Processor Response
Command Selection Process	Command Search Request	Satisfactory Command Search
Command Execution Process	New Command Started	Stimulus-Response Association
Command Buffer	Current Command Backlog	Consider Attention Reallocation

These relationships are also shown in Figure 2. It should be remembered that requests for the functions indicated in Table 2 are handled on a first-come, first-served basis, and therefore, the functions are not always performed immediately upon request. Requests for Performance Monitoring and the Excessive Error Process are not shown because Performance Monitoring occurs in alternation with the other functions and initiates the Excessive Error Process when performance is unacceptable. The sections below detail the functions of the Supervisory Processor.

a. The Stimulus-Response Association Process. The Stimulus-Response Association Process updates the contents of the Command Memory. It will be recalled that the Command Memory is an array, the rows of which correspond to all possible desired task controller outputs, and the columns of which correspond to all possible current task controller outputs. The content at each array location is the command for input to the task controller necessary to cause its output to transition from a current state to a desired state in one Command Operative Time.

The Stimulus-Response Asociation Process is responsible for entering the commands into the Command Memory at appropriate locations. To do this, it must have information about sequential task controller outputs (i.e., cursor positions) and the task controller inputs (i.e., control stick positions) which intervened between pairs of outputs. In the ideal case, this information is obtained as follows.

At time t_i, a "new command started" signal is provided to the Supervisory Processor by the Command Execution Process. At this time, the Stimulus-Response Association Process records the current task controller

output and current command to the task controller as provided by the Perception Process. Later, at t_{i+1}, (where t_{i+1} minus t_i is the Command Operative Time), the "new command started" input is presented to the Supervisory Processor once again. At this time the Stimulus-Response Association Process again records the current task controller output and current command to the task controller. With these two records the Stimulus-Response Association Process can now update the Command Memory in the following manner.

The task controller output at t_i and the task controller output at t_{i-1} are used as column and row indicators for positioning the intervening command in the Command Memory. The command at t_{i-1} is inserted in the array at this location, as shown in Figure 7.

At t_{i+1}, the "new command started" input arrives at the Supervisory Processor once again and the Stimulus-Response Association Process records the value of the task controller output and command input to the task controller for this instant in time. The Stimulus-Response Association Process therefore works with two time samples of data: the first being presented by the Perception Process at the present time and the other being one which is remembered by the Stimulus-Response Association Process as having been recorded by the Perception Process at a previous instant in time. The Stimulus-Response Association Process is depicted in Figure 8.

This description of the function performed by the Stimulus-Response Association Process has assumed ideal conditions -- ideal in the sense that when the "new command started" input arrives, the Supervisory Processor is free and able to immediately execute the Stimulus-Response Association function. In reality, this is usually not the case. The Supervisory Processor is almost always engaged in performing one function or another, and the "new command started" input is loaded into a queue. The result is that Stimulus-Response Association is delayed, so the task controller output and command input used to update the Command Memory are not necessarily those which were present at the instant when a new command began execution. There is, therefore, a certain amount of inaccuracy in the data used to update Command Memory. For this reason, new entries into the Command Memory are always averaged with entries which have been previously stored at that location. Because of this averaging, HOPE (likewise, the human) becomes adept at particular tasks only after a certain amount of practice. Only through repeated observations of the same situation is the error in the recording process finally eliminated.

b. The Satisfactory Command Search Process. The purpose of this function is to provide a command when the Command Selection Process is unable to do so. The Command Selection Process indicates its need for help by submitting a request for a Satisfactory Command Search to be handled by the Supervisory Processor.

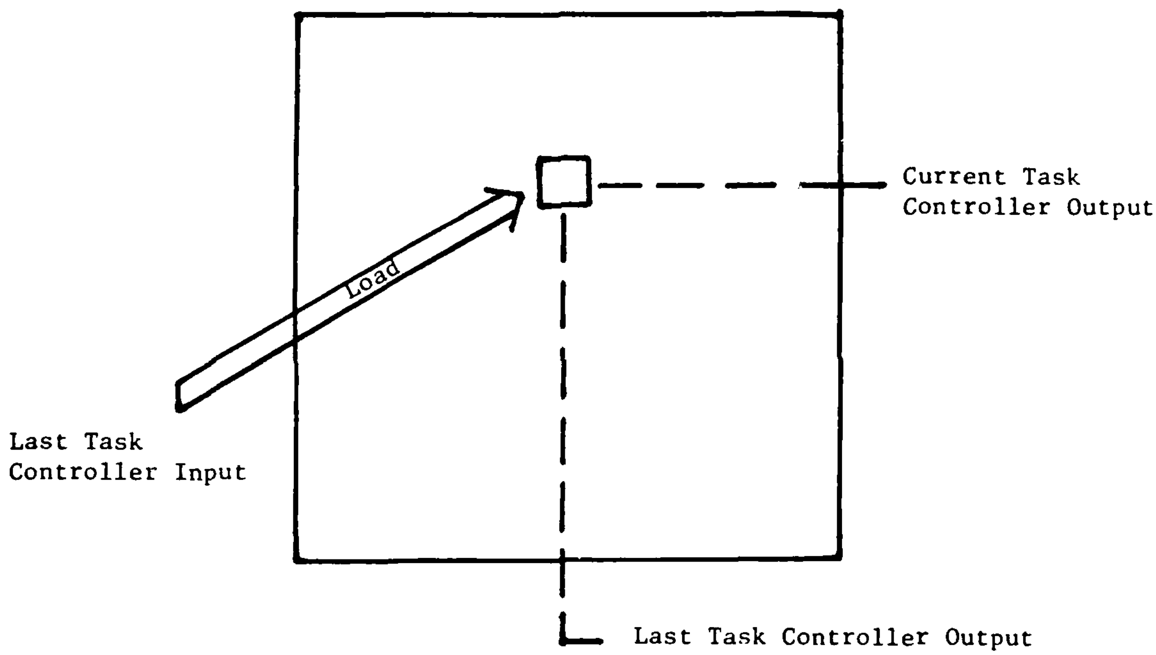


Figure 7. Command Memory Loading Resulting From Stimulus-Response Association Process

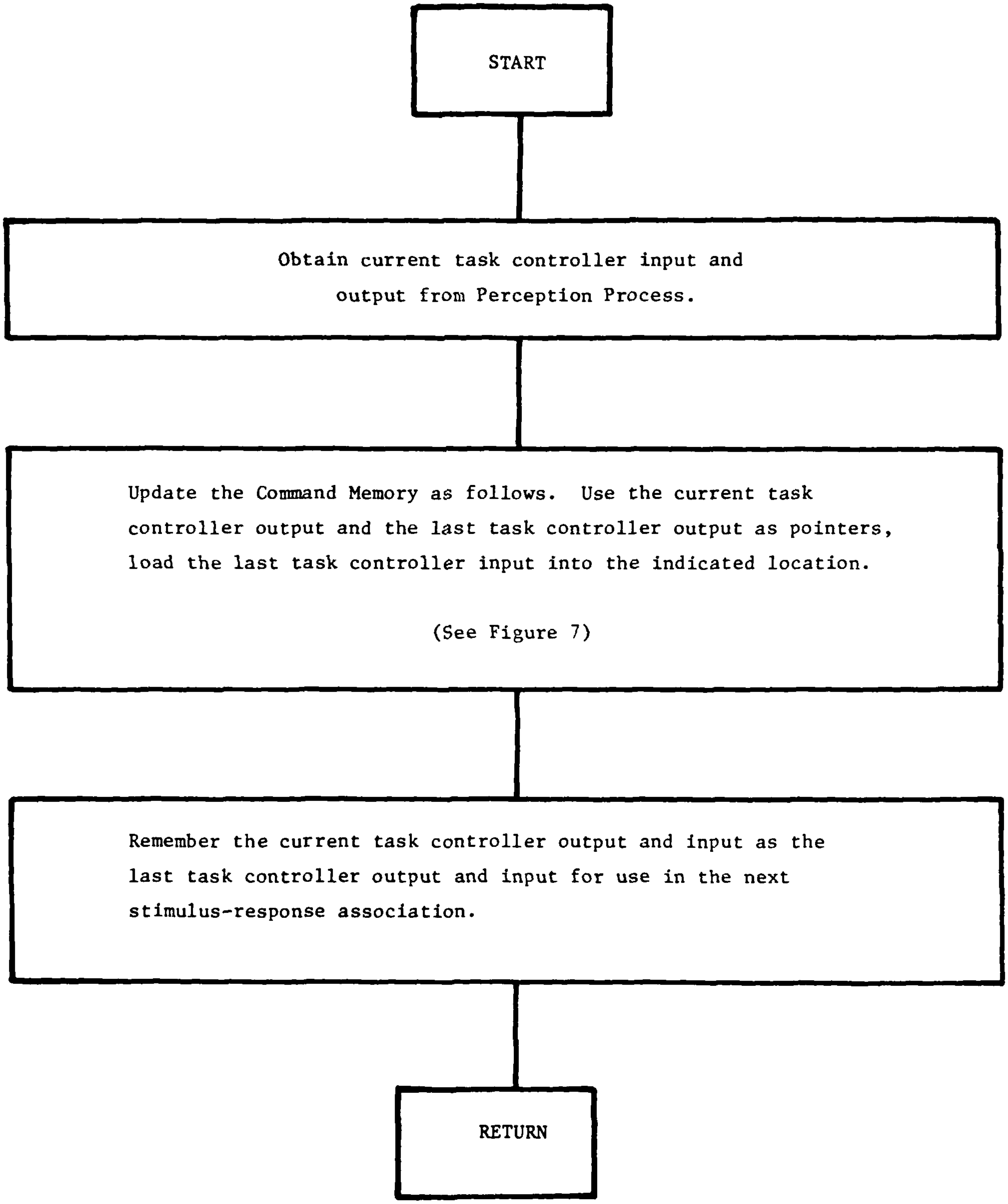


Figure 8. The Stimulus-Response Association Process

In a very limited sense, the Command Selection Process performs a search for a satisfactory command within the Command Memory. This search is limited to only one location within the Command Memory, namely, that pointed to by the last predicted state and the desired state. The Satisfactory Command Search Process then performs a more extensive search within the Command Memory in an attempt to locate a command which may not be the best command for the particular situation in question, but which will provide acceptable results. Acceptable here means that the predicted result of using such a command differs from the desired state by less than the acceptable position error, as dictated by one of three Control Strategy Parameters, ERRLIM.

The search of the Command Memory by the Satisfactory Command Search Process is carried out in two stages. The first stage is called a column search. This portion of the search is shown in Figure 9. The column to be searched is the column indicated by the last predicted state. The region to be searched is the region bounded by the desired state minus ERRLIM and the desired state plus ERRLIM. The search progresses outwardly from the location pointed to by the desired state and last predicted state as shown in the center column of Figure 10. The location in the center of the column to be searched is the location of the situation for which a command is needed. The search expands outward from this location in the sequence C1, C2, C3...as indicated in Figure 10. This column search continues until either a command is found or the region boundaries are encountered. If a command is found, this command is provided to the Command Selection Process for loading into the Command Buffer. If no command is found before reaching the region boundaries, a broader search called a block search is undertaken.

The search region for this more extensive Satisfactory Command Search is indicated in Figure 11. Here the limits of the search are the same in the row dimension, i.e., the desired state plus ERRLIM and the desired state minus ERRLIM; but the column limits are expanded to include the last predicted state minus ERRLIM through the last predicted state plus ERRLIM. The sequence of this search continues until a command is found or until the region boundaries are encountered.

Because the task controller output is, or is expected to be, in the state labeled last predicted state, precise assessments can be made of the suitability of any command found in the column search. In other words, the task controller has not been observed in this situation, but has been observed in situations which are sufficiently similar to allow assessment of the expected result of a particular course of action. The rationale for block search is a bit more vague. Here, the task controller has not been observed, nor is it expected to be, in any of the states offset from the last predicted state at the time instant in question. In other words, in addition to some tolerance on the resulting predicted state, X_{ti}, there is also lack of specificity about the description of the beginning state, X_{ti-1}. This implies the assumption that all task controllers which will be

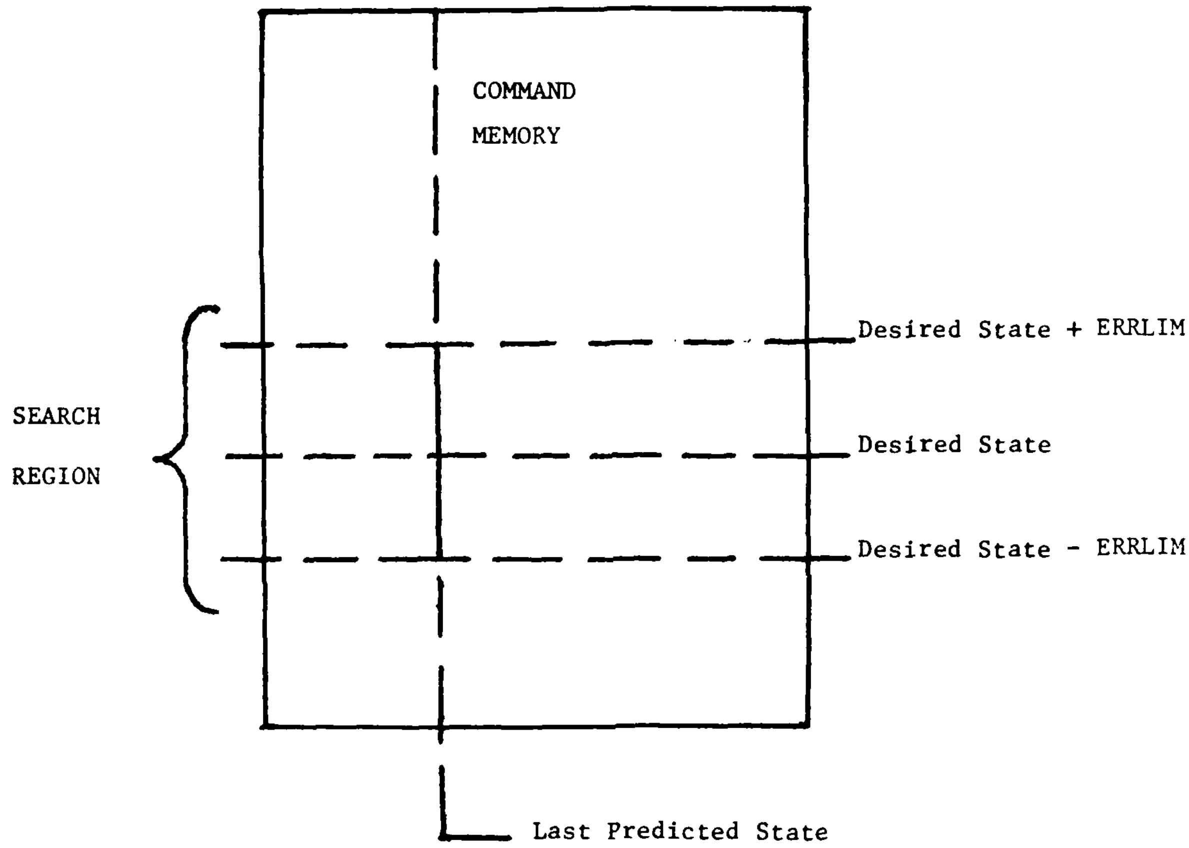


Figure 9. Satisfactory Command Search Process -- Column Search

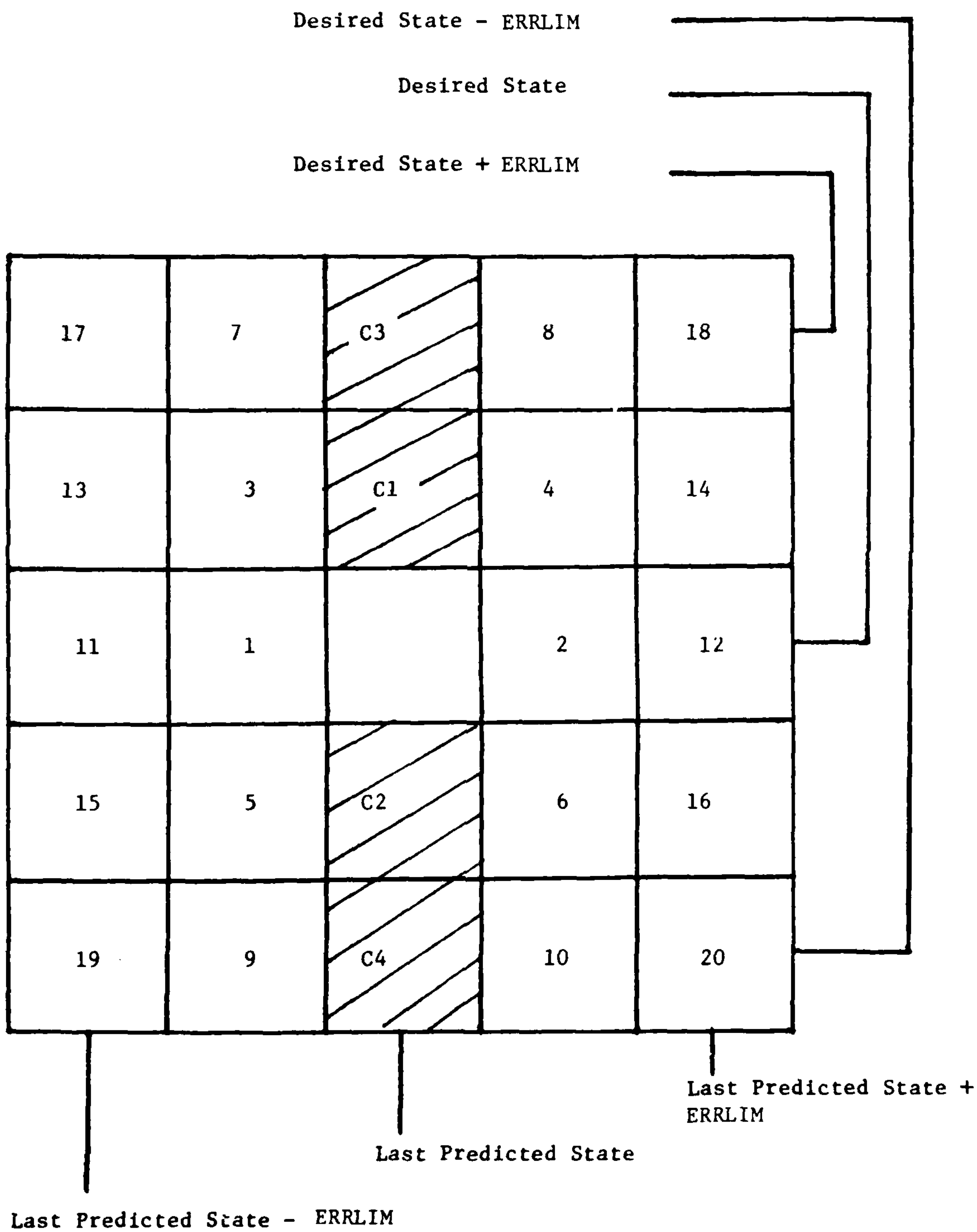


Figure 10. Block Search Sequence Detail --Cross-hatched area indicates region searched in Column Search

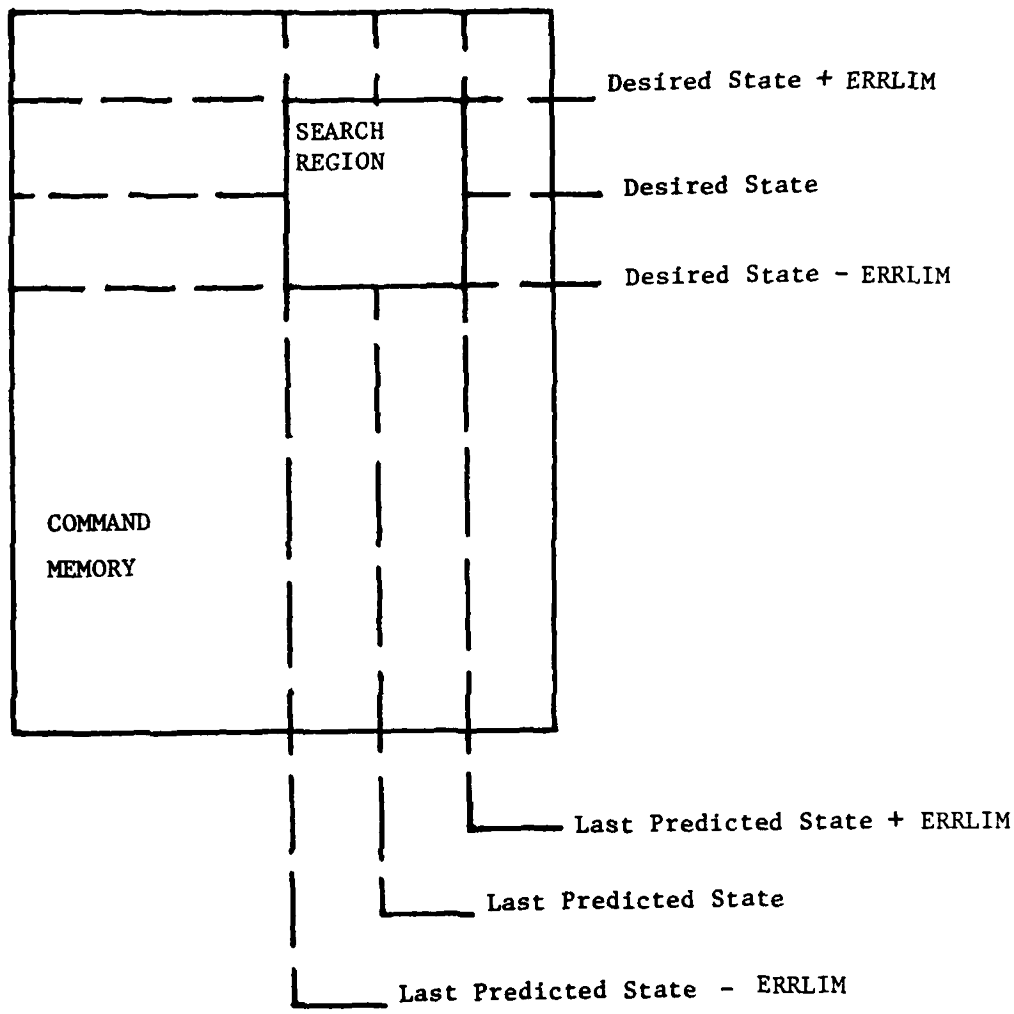


Figure 11. Satisfactory Command Search Process -- Block Search

encountered are reasonably analytically continuous; that is, within a "small" region, if the current state is offset by some amount, "a" (last predicted state = X_{ti-1} + a), then the resulting state will also be offset by an amount, "a" (predicted state = X_{ti} + a), for any command found within the region bounded by ± a.

The Satisfactory Command Search Process must still produce a command for the Command Selection Process, even if neither the column search nor the block search discovers one. When these two search procedures fail, the Satisfactory Command Search Process resorts to what might be termed a "best guess" approach. In this instance, the Satisfactory Command Search Process implicitly assumes that the task system is a zero-order device with no gain, lead, or lag. This type of device has the characteristic that the task controller output at t_i is equal to the task controller input at t_i regardless of any past conditions. The command provided to the Command Selection Process in this condition is simply the desired state.

The results of applying these "best guess" commands are unpredictable to some degree. Therefore, when such a command is provided to the Command Selection Process for entry into the Command Buffer, the Supervisory Processor is informed so that it cannot divert attention from the task. This point will be elaborated in discussion of the Attention Reallocation Process. The overall structure of the Satisfactory Command Search Process is shown in Figure 12.

c. The Attention Reallocation Process. As currently implemented, switching of attention away from the tracking task is allowed when the backlog in the Command Buffer exceeds some level, or when commands have been planned for all states out to the maximum preview available. When either of these two criteria are met, the Supervisory Processor is requested to apply the Attention Reallocation Process to divert its attention to other tasks. Before attention is diverted, however, the Supervisory Processor determines if there are "best guess" commands in the Command Buffer. If so, attention is not diverted. If there are no "best guess" commands in the buffer then attention is diverted from tracking. Since HOPE's Perception Process currently inputs only visual information, diverting attention from tracking diverts the Perception Process, and thus stops the Command Selection Process. Attention is switched back to tracking when there is only one command remaining in the buffer, and Command Selection must continue (see Figure 13).

d. Performance Monitoring and the Excessive Error Process. As described above, one of the functions of the Supervisory Processor is performance monitoring. Performance monitoring, very simply, consists of detecting when the task controller output is different from the desired output (desired state) by an amount greater than the acceptable error criterion (ERRLIM). This function is performed in alternation with each of the other Supervisory Process functions. If an unacceptable error is detected, the Performance Monitor immediately invokes the Excessive Error Process.

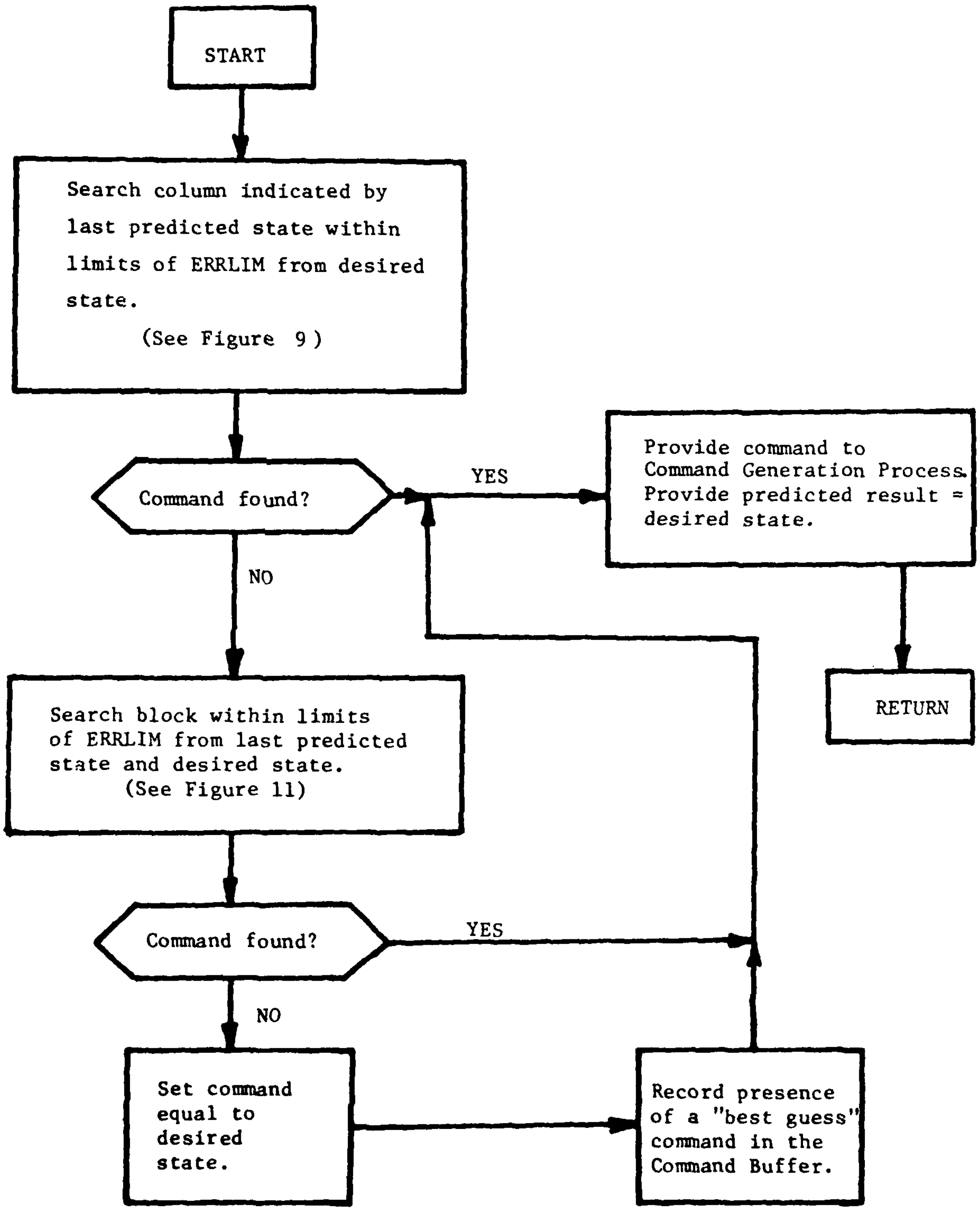


Figure 12. Satisfactory Command Search Process

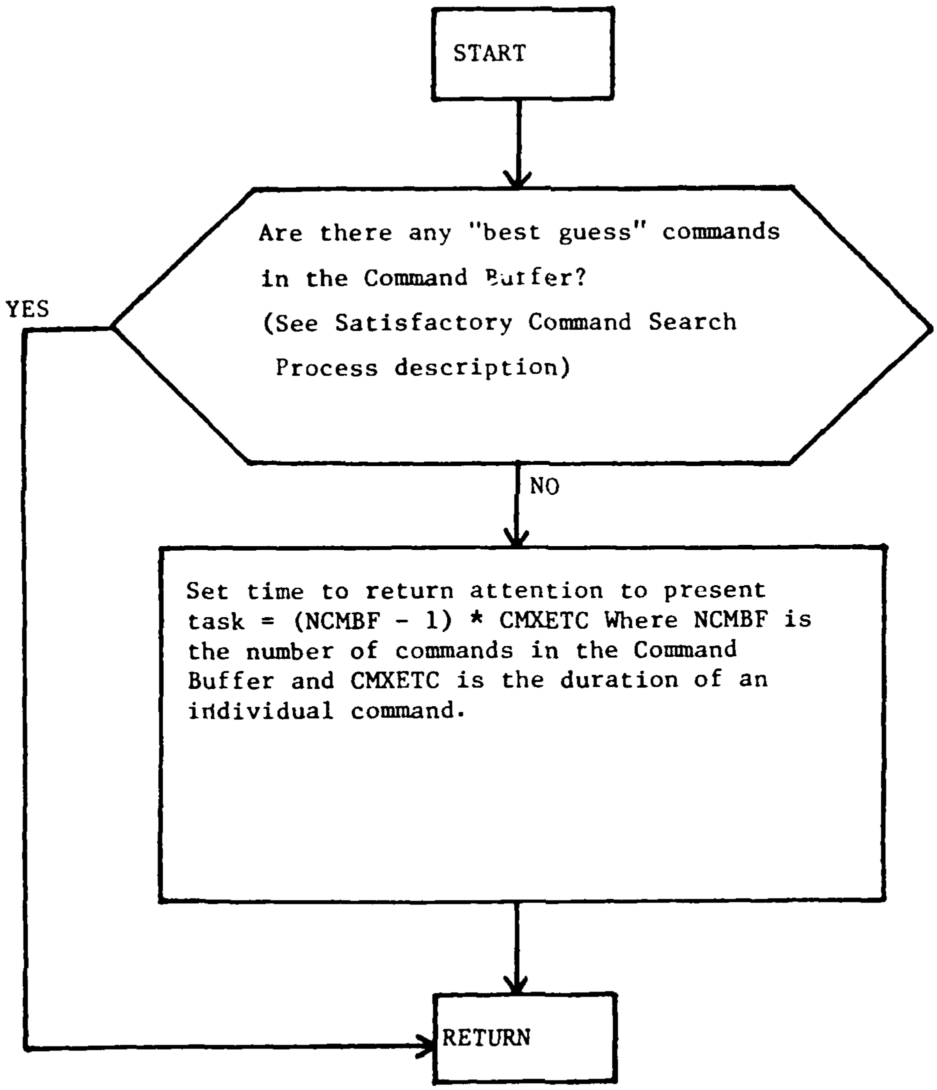


Figure 13. Attention Reallocation Process

If an unacceptable error is detected, there has been some deficiency in planning (i.e., in command string generation) in the past; hence, all commands remaining in the Command Buffer are suspect. Therefore, the first step taken by the Excessive Error Process is to empty the Command Buffer. Also, because of the assumed planning error, any requests in the Supervisory Processor queue are also suspect and are also dumped to allow for expeditious handling of any new requests which might appear during the course of correcting the excessive error. The next step taken by the Excessive Error Process is to set the last predicted state equal to the present state, i.e., to force command string development to begin all over again from the present state.

Next, the Excessive Error Process acts for the Command Selection Process and attempts to find the currently needed command in the Command Memory. If a command is found, the Excessive Error Process places the command directly in the Command Buffer, sidestepping the Command Selection Process. It does, however, report the predicted result of using this command to the Command Selection Process for its use in continuing the command string generation process. If a command is not found at this location, the Excessive Error Process produces a "best guess" command, assuming that the command needed to get to the desired state is the desired state itself.

The effect of using this type of command is not generally predictable and may not compensate for the error. To eliminate re-selection of "best guess" commands which do not compensate for an error, further "best guess" commands are adjusted prior to use. For example, if the cursor is presently off the track on the same side as the last time the Excessive Error Process was invoked and no command was found in the Command Memory, this adjustment is made by adding a factor to a cumulative adjustment factor, which is then added to or subtracted from the "best guess" command. The increment by which the cumulative command adjustment factor is increased is computed on the basis of one of the control strategy parameters, referred to as ADJUST. If the cursor is not off the track on the same side as last time, then the cumulative adjustment factor is set to zero, and the "best guess" command is used as is. Figure 14 shows the command adjustment procedure.

Whether the Excessive Error Process finds a command in the Command Memory or has to fabricate one, the command is placed directly into the Command Buffer, and the predicted result is provided to the Command Selection Process. For both command types, the predicted result is the desired state. If the command was obtained from the Command Memory, this result is predicted quite accurately; in the case of use of a fabricated command, the result is less accurately specified.

The Performance Monitoring Process operates in alternation while other processes are being executed. Hence, after the Excessive Error Process terminates, it would be quite possible for the Performance Monitor to detect the same problem that the Excessive Error Process just

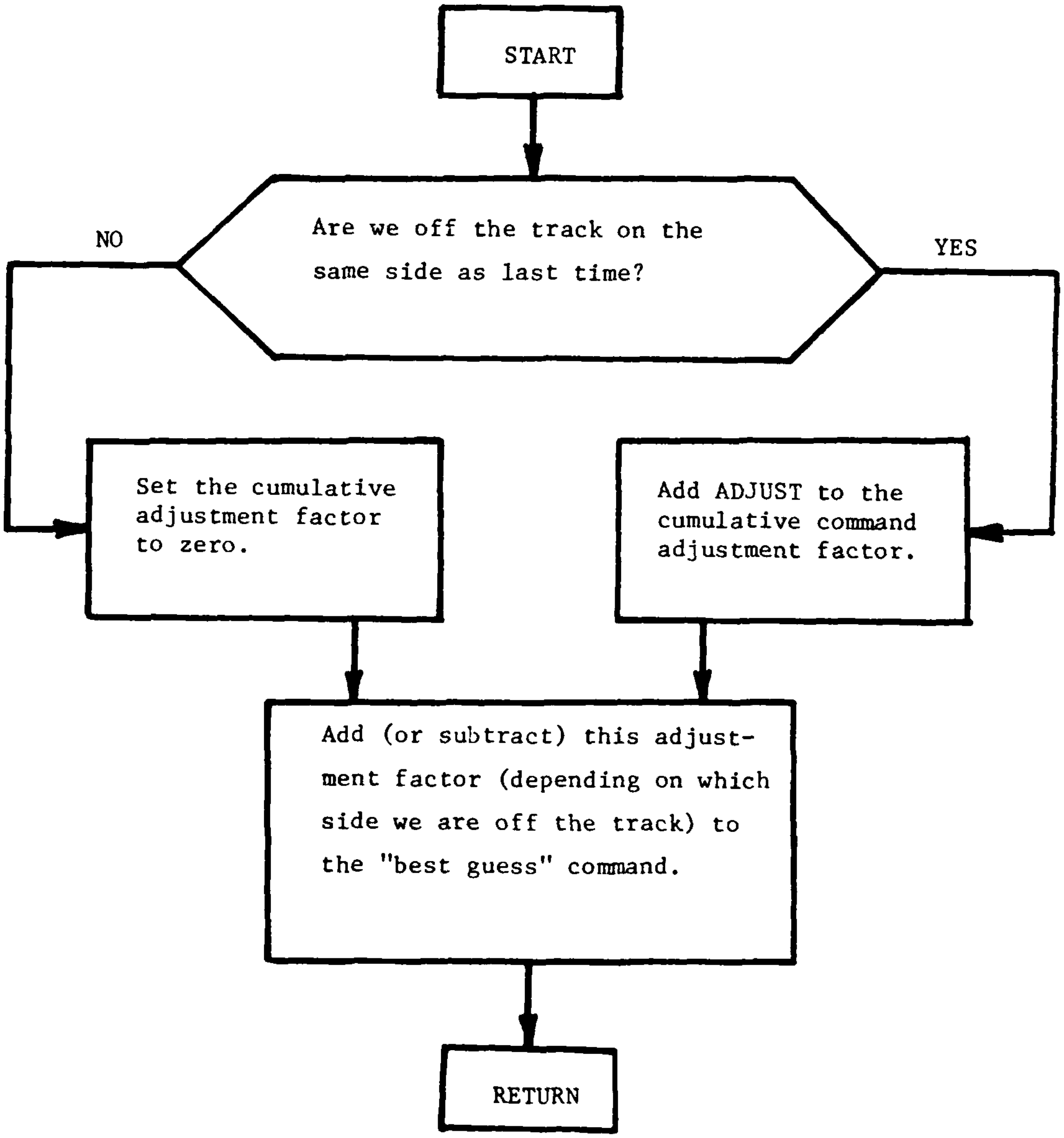


Figure 14. Command Adjustment Method

attempted to rectify and invoke the Excessive Error Process once again. If this were allowed to occur, no commands would ever get into the Command Buffer, no process requests would ever get into the queue, and the net effect would be that no progress would ever be made toward eliminating the excessive error. This situation does not normally occur. Therefore, it was necessary to design HOPE to ignore the repeated reports of intolerable error until there has been time for assessment of the effects of corrective steps. This has been implemented by not allowing the Excessive Error Process to repeat until two Stimulus-Response Association requests have been received. The Stimulus-Response Association requests are counted from the time the excessive error was detected. In this manner the Supervisory Process is assured that the command which it placed into the Command Buffer has been executed so that it is now appropriate to reassess the situation, if the Performance Monitor still claims there is a problem. The overall structure of the complete Excessive Error Process is shown in Figure 15.

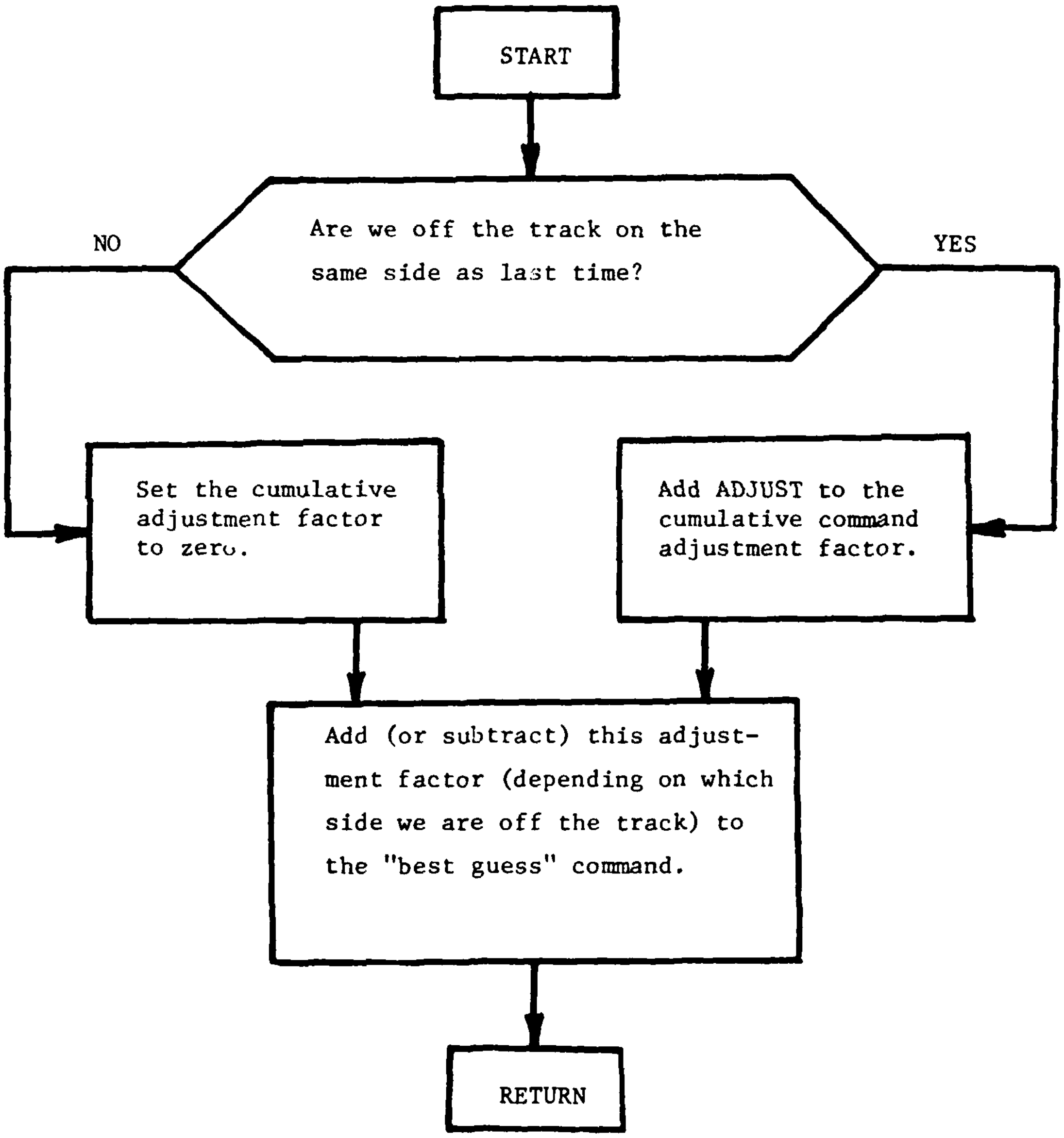
7. Controlling Parameters - Fixed Process Timing

One final feature necessary for the implementation of HOPE is the simulation of process execution and intercommunication times. The Perception, Command Selection and Command Execution Processes and the processes executed by the Supervisory Processor require a finite amount of time for execution. The exact length of time which each process requires will be discussed below, after description of the implementation of these processing times in the model.

Figure 16 shows the standard process timing structure in which each of the HOPE processes is embedded. Each time through the program, every process is called through its process timer. If sufficient time has elapsed since the last time this process was executed, then the results of the last execution are made available and the process is allowed to execute again. The timer is then reset to simulate the time required to perform this function.

Figure 17 shows the overall program structure. The main control block sees to it that every process is called during each loop through the program so that all process timers are updated. Any process whose timer expires in a given time through the program has the results of its last execution made available to other processes which might use this information, thereby simulating intercommunication between processes.

Standard process timers control the amount of time required to execute the Perception, Command Selection, Stimulus-Response Association, Satisfactory Command Search, Attention Reallocation and Excessive Error processes. The simulated real time taken to execute each of these processes is based on physiological data.



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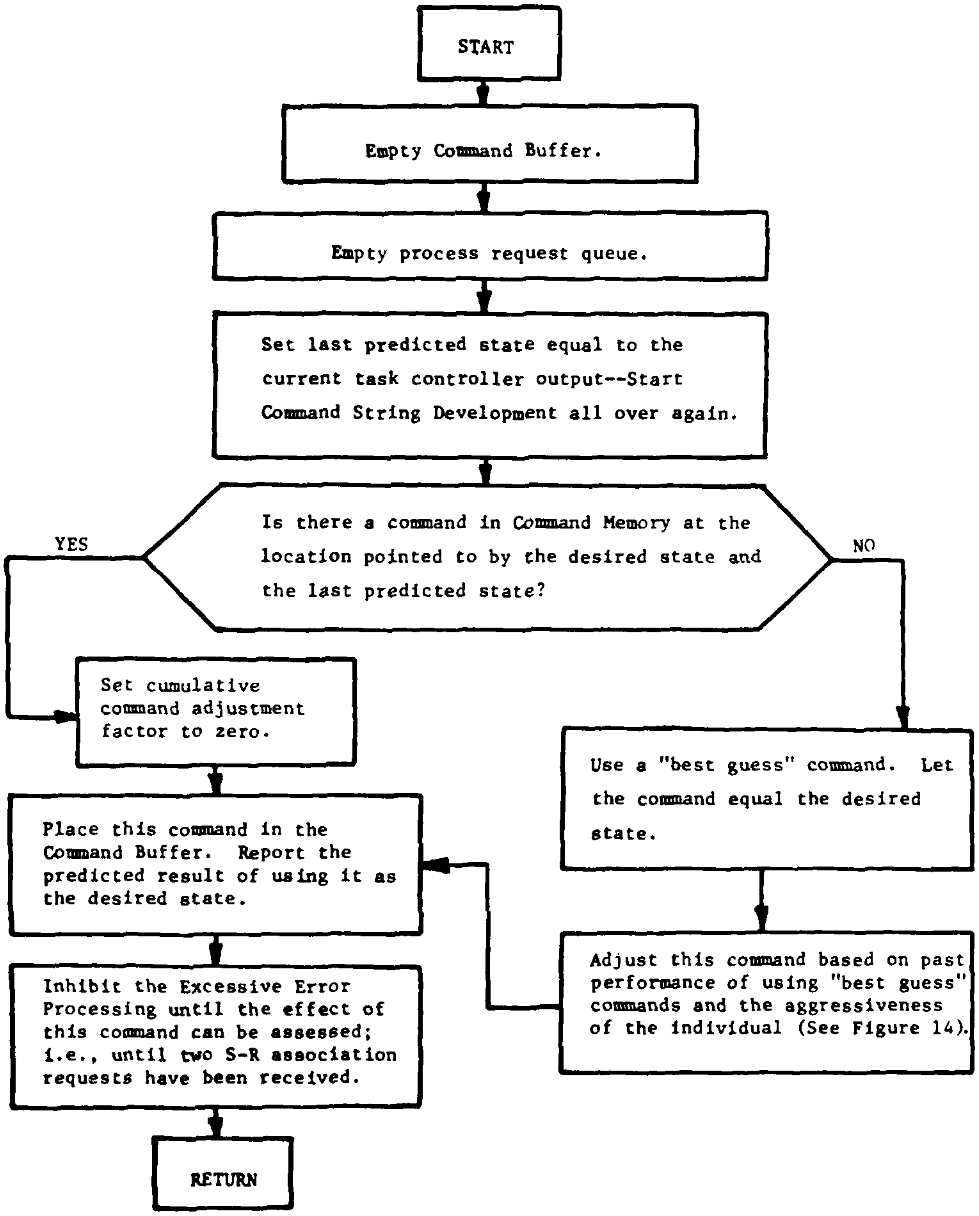

Figure 15. Excessive Error Process

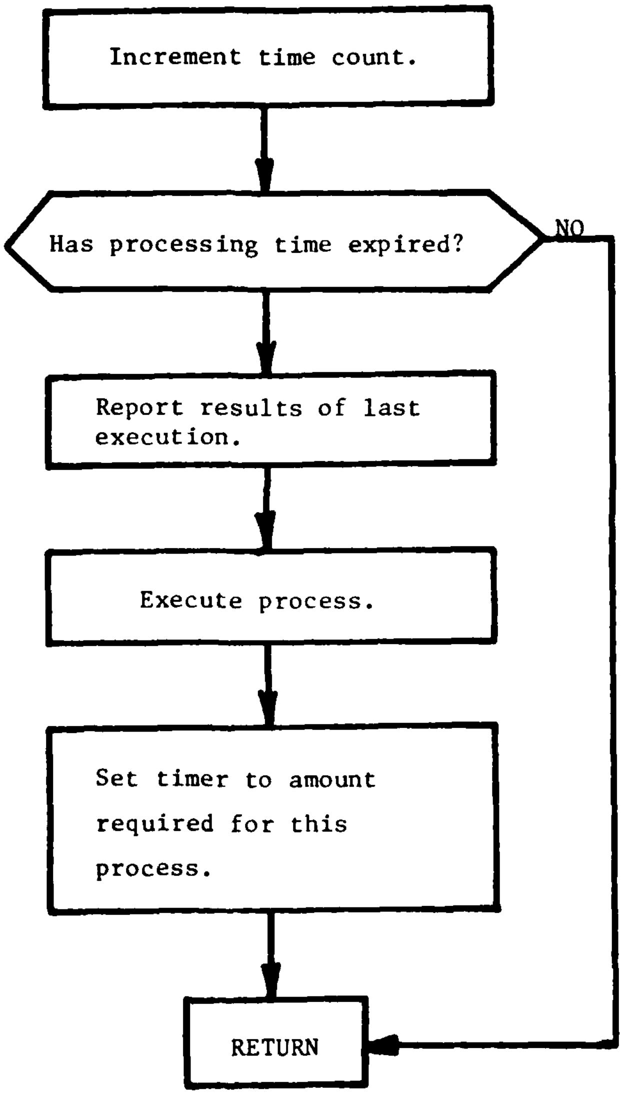

Figure 16. Standard Process Timer Structure

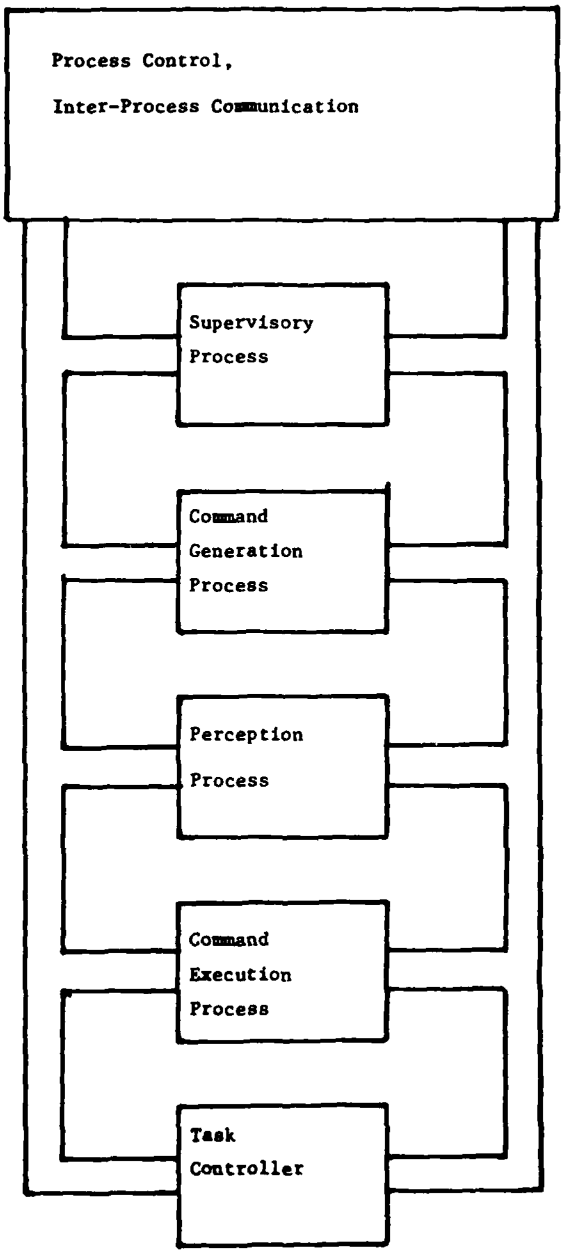

Figure 17. HOPE Software Organization

The perception interval is based primarily on sensory neural transmission speed. For an average distance of 1 m and an average transmission speed of 25 m per sec, typical transit time for perceptual information is in the neighborhood of 40 msec. This is the length of time required for information to be transmitted from the receptor to the brain which uses it. Hence, the Perception time interval in the model is set at 40 msec.

The time required for the selection of an individual command is based on neural transmission speed and on the results of reaction time experiments. Typically, the results of binary choice reaction time experiments lie in the range of 120 to 180 msec. This time is composed of three elements: the perception time, the response selection time, and the response transmission and execution time. In a manner similar to that used to evaluate the perception time, motor neural transmission time is evaluated to be in the neighborhood of 50 to 60 msec. This leaves between 30 and 60 msec for the actual response selection process. The HOPE model currently uses 40 msec for the Command Selection Process time.

The processing time required for the Satisfactory Command Search Process is also determined from neural transmission speeds and reaction time experiments. In this case, the appropriate course of action is not known beforehand and must be determined at the onset of the stimulus. Results for this type of behavior typically lie in the range of 240 to 300 msec. Assuming that the sensory and motor transmission times remain fixed means that the command selection time has increased by 40 to 80 msec over the binary choice reaction time requirements. The execution time requirement for the Satisfactory Command Search Process is therefore set at 120 msec.

The Stimulus-Response Association Process is the reverse of the Command Selection Process. The Command Selection Process takes a command out of the Command Memory; the Stimulus-Response Association Process puts a command into the Command Memory. For this reason, the Stimulus-Response Association Process execution time is set equal to the Command Selection Process time, i.e., 40 msec.

The most difficult process execution time to rationalize is the Excessive Error Process time. This process must allow time for emptying the Command Buffer, for emptying the process request queue, and for performing the same function as the Command Selection Process -- with the addition of the command adjustment function. It should therefore take at least as long as the Command Selection Process. The time required for discarding the old command string and for dumping all previous processing requests is probably insignificant by comparison. Adjustment of a best guess command could perhaps take a measurable amount of time -- perhaps as long as the Satisfactory Command Search Process. One could argue then that the time required for this process should be in the range of 40 to 120 msec. Currently, the execution time for this process is set for 40 msec.

Studies of attention switching have not been pursued at this point. Therefore, an execution time for the Attention Reallocation Process has not yet been established.

8. Controlling parameters--Control Strategy Parameters

One of the fundamental assumptions in the design of HOPE is that continuous control behavior is modulated by an individual's control strategy. Control strategy is realized in HOPE by means of control strategy parameters (CSPs). In HOPE, three CSPs have important effects on the timing and style of tracking behavior. The CSPs are: the time over which one command is executed, or Command Operative Time (COT), an operator-defined limit for the amount of error allowable (ERRLIM), and the magnitude of response to excessive error (ADJUST). Each will be discussed below in terms of the way its variation affects the simulation HOPE.

a. Command Operative Time (COT). The theory of psychomotor behavior which shapes HOPE contains an explicit assumption that humans execute motor control with short commands whose duration can be controlled by humans. This is thought to be an aspect of control strategy and would be evidenced in the human by the inverse of the frequency of firing of neurons controlling the limb involved in the control task. The limb controlled would exhibit some degree of "jerkiness", or "bang-bang" control, when the duration of commands was relatively long. In the HOPE simulation, this aspect of control strategy is represented by a variable parameter called Command Operative Time (COT).

COT value has important effects on the behavior of HOPE. It will be recalled that the Stimulus-Response Association Process is signalled only when the Command Execution Process begins executing a new command. If COT is short, then each command execution occurs relatively quickly, and there are frequent signals for the Stimulus-Response Association Process. Also, if COT is close to the Command Selection Process time of 40 msec, the number of commands in the Command Buffer will always be small, since each is executed nearly as rapidly as it is generated. Longer COT values permit command strings of several seconds in duration to build up in the Command Buffer. The size of COT also has direct effects on the way in which the Command Memory develops, since the associations which occur are of events perceived as one COT apart in time.

Prior to the validation procedures described in Section V, five values of COT were selected for testing in HOPE. These were: 40, 80, 120, 160, and 200 msec.

b. Operator Defined Accuracy Criterion -- ERRLIM. The theory on which HOPE is based assumes that a second aspect of control strategy in continuous manual performance is the degree of error that an individual will allow before major error corrective action is initiated. Some individuals show considerable error before they begin to pay special attention to correcting error; other individuals allow themselves much

less error before corrections are begun. In HOPE, this aspect of control strategy is represented by ERRLIM -- the amount of position error allowed before the Excessive Error Process is signalled. As ERRLIM decreases, the frequency of interrupts by the Excessive Error Process increases. Also, as ERRLIM decreases, there is a decrease in the region of the Command Memory search during a Satisfactory Command Search.

A major impact of ERRLIM in HOPE is on the average command string length. The smaller the ERRLIM, the more frequently the Excessive Error Process interrupts and dumps the commands in the Command Buffer. For small error tolerance, i.e., small values of ERRLIM, the average command string length remains very small early in learning when the command memory is not loaded with good commands for accurately predicting future control actions. As learning continues, the command memory fills with good commands, and the average command string length continues to increase, almost independently of ERRLIM.

A second impact of ERRLIM on the simulation is that observable error performance generally increases with ERRLIM, for a given state of learning. The state of learning is indirectly measurable in HOPE as the average number of Satisfactory Command Searches in a given interval of time. For two models with different ERRLIMS and comparable average numbers of Satisfactory Command Searches, the model with the larger ERRLIM will demonstrate larger actual errors. This is because during the Satisfactory Command Search, the model with the larger ERRLIM can select commands which are further from the next desired state and, therefore, more likely to result in observable error. With a large ERRLIM, the command string in the buffer is composed of commands known a priori to produce larger task controller output errors.

This effect is greatly diminished as learning increases. One reason is that there are fewer demands for the Satisfactory Command Search, and thus fewer opportunities for selecting an "acceptable" command which produces considerable error. In addition, as learning increases, even when the Satisfactory Command Search does occur, commands will be more frequently found closer to the location of the needed command. These commands are less likely to result in large errors.

Prior to the experimentation described in Section V, five values of ERRLIM were selected for testing in HOPE. These were .58, 1.17, 2.34, 4.67, and 9.35 cm.

c. Magnitude of Response to Excessive Error -- ADJUST. The third control strategy parameter represented in HOPE is ADJUST. In human control behavior, responses to conditions of excessive error vary in size. A confident individual may exert large movements to try to compensate for an error. A more conservative individual may apply smaller movements. HOPE assumes that one aspect of an individual's control strategy is the magnitude of the response to excessive error, which is represented by ADJUST.

The manner in which ADJUST affects HOPE behavior is as follows. Each time the Excessive Error Process is called, it attempts to find a valid command in the Command Memory. When this fails, it provides the current desired state (a "best guess" command) or some modified version of it. ADJUST is used in the modification of the "best guess" command.

Modified commands are used when two conditions are met: (a) the error has been excessive in the same direction, relative to the track, since the last time the Excessive Error Process was called (at which time no command was found in the Command Memory) and (b) no command is found in the Command Memory for the current situation. The Excessive Error Process records the number of times it sequentially operates with the use of "best guess" commands without achieving acceptable error.

Modification of a "best guess" command is performed by adding (or subtracting, depending on the direction of the error) a factor to the best guess command. The factor is the product of ADJUST and the number of sequential calls for the Excessive Error Process. This produces the effect of initiating increasingly bold moves in the face of persistent error.

The procedure of adding multiples of ADJUST repeats until the observed error is in the opposite direction from that which previously signaled the Excessive Error Process. At this point, the counter is zeroed. The counter is also zeroed whenever the Excessive Error Process enters the Command Memory at a point where a good command exists. In such a case, the command found in memory is used as the next command.

The impact of ADJUST on model behavior is subtle. Both extremes of the parameter, in general, will result in relatively greater error than moderate values. For very small values of ADJUST, the "best guess" command, (i.e., the currently desired next state) dominates model behavior in novel situations and rapid correction of errors is not observed.

For very large values of ADJUST, the currently desired next state contributes a minor part to the model behavior in novel situations, and jerky, erratic behavior results. The experience base expands rapidly with time with such behavior, however, and is not confined closely to the track's centroid of history. Because of this phenomenon, models with large values of ADJUST may show less error in response to new track positions since the bolder moves associated with a large ADJUST may have exposed HOPE to these positions.

Three values of ADJUST were selected for use in testing HOPE. These were of .58, 1.46, and 2.34 cm. Thus, when ADJUST equals .58, for example, the first time error is excessive in a given direction, .58 multiplied by 1 will be added to the "best guess" command. If the error remains excessive in the same direction, .58 multiplied by 2, will be added to a "best guess" command.

9. HOPE Program Specifications

The HOPE program is written in ANSI Standard FORTRAN and has been used on both the CDC Cyber 70/74 and Interdata 7/32 computers at Georgia Tech. The program consists of 950 lines of code and requires less than 30K words of central memory for execution. No overlays or disc-based data are necessary. The program currently runs about 12 times faster than real time.

SECTION V

PRELIMINARY TESTING AND RESULTS

A. Introduction

This section describes an experiment and data analyses performed in an attempt to provide initial validation and demonstration of HOPE, (Human Operator Performance Emulator). HOPE is a computer simulation which models cognitive processes associated with psychomotor skill learning and the effects of control strategies which individuals might employ during learning. The processes modeled relate to perception, learning, retrieval from memory, response selection and execution, and performance monitoring.

HOPE can model performance guided by different control strategies. Control strategy is represented in terms of three control strategy parameters (CSPs): ERRLIM, ADJUST, and COT. These parameters dictate, respectively, the amount of error allowed before major error correction procedures are applied, the magnitude of adjustment performed in excessive error conditions, and the length of time over which one motor command is active. Five values of ERRLIM, five values of COT, and three values of ADJUST were tested, yielding a total of 75 (5 X 5 X 3 = 75) sets of CSP values. Using numerical input corresponding to each of four different training conditions, HOPE was run 75 times, each time guided by a different control strategy, as represented by a set of CSP values. Thus, for each training condition, HOPE produced 75 predictions of control stick motions. The term "HOPE model" will be used to refer to the operation of HOPE when controlled by a particular one of the 75 sets of CSP values.

The basic task used in testing was a one-dimensional preview tracking task. Human subjects used a low friction isotonic stick to control the position of a cursor, specifically to try to center the cursor on a track traveling on a screen before them. The control function was position type, with a non-linear first order lag. It is this control function which was to be learned by the subjects and by the HOPE models. Subject behavior was recorded and matched against behavior of HOPE models modulated by different control strategies. The control strategy parameters used in the HOPE model which best predicted human behavior in a given time bin were used to infer the control strategy for that subject during that period in time. This matching procedure will be described later in greater detail.

There were three basic questions examined in this initial testing. The answers are important for establishing HOPE as an accurate simulation of psychomotor behavior and for validating the approach of using control strategy identification as a means for measuring human progress in training. The three questions are listed and discussed below.

<u>Question 1</u>: Do HOPE models match human behavior to an acceptable extent?

There already exist adaptive engineering models with time-varying coefficients which produce matches of certain types of behaviors. To validate HOPE as an alternative approach, it is critical that HOPE also be able to match human behavior well. For this experiment, the criterion for "acceptable" matching of human behavior by HOPE was as follows: For at least 90% of the subjects, one or more HOPE models must match human behavior with a root mean square difference score of less than 7.5 cm for at least half of the duration of the testing (i.e., at least 30 out of the 60 time bins). This difference score requires that HOPE match human behavior within 20% of the control stick's range of motion.

<u>Question 2</u>: Does control strategy, as identified by HOPE, change with learning?

Earlier discussion (see Section III) pointed out that control strategy is believed to change during the learning of a new psychomotor task. Most individuals begin a new psychomotor task using relatively ineffective strategies for performance. Such strategies may be poorly defined, or they may be well defined, based on experiences with other, different tasks. With practice, the initial control strategy is revised, and a more effective strategy develops. As was pointed out earlier (see Section III), practice allows certain processes to become less demanding of attention, freeing more attention for the development of an appropriate control strategy.

If the conceptualization of control strategy in HOPE is valid, then human control strategy as identified by HOPE should change with learning. That is, the control strategy parameters (CSPs) of the HOPE models which best match human performance should change with learning.

For this preliminary testing, subjects were given five 4-minute trials of the preview tracking task. Control strategy was said to have changed with learning if the CSPs of the best match models for behavior on the first trial were significantly different from those for behavior on the fifth trial.

<u>Question 3</u>: Does control strategy, as identified by HOPE, reflect differences between training conditions?

Another assumption underlying the definition of control strategy is that it reflects variations in the training environment. When factors

such as task difficulty or available cues change, control strategy gradually changes so that overt behavior can remain fairly effective. For example, a driver can stay on the road fairly successfully in dry weather, or in a snowstorm, if he adaptively modulates his strategy for driving, e.g., his speed, his accelerations, etc.

If the conceptualization of control strategy in HOPE is correct, then control strategy as identified by HOPE should reflect differences between training environments. In the present experiment, the training environment was varied in two independent ways to create four distinct training environments, each maintaining the same non-linear control dynamics. First, subjects tracked either a more rapidly varying ½ Hz track, or a less rapidly varying ¼ Hz track. These two tracks make different demands on the human operator, just as driving on a curving road makes demands different from driving on a straight road. For example, motor commands must vary more rapidly when tracking a more rapidly changing track or road. In HOPE, such changes might be reflected in changes in COT, which controls the frequency with which motor commands can vary. It might be predicted that the COTs of the best fit models for ½ Hz tracking behavior would have shorter values, allowing more frequent execution of new commands.

Further, a more rapidly curving track should cause subjects to make more energetic responses to excessive error, since the track is likely to be moving away from the controlled element at a more rapid rate in errorful conditions. This idea suggests that ADJUST values of best-fitting HOPE models should be larger in ½ Hz track conditions than in ¼ Hz track conditions.

A second way in which training conditions varied was in terms of tracking guidelines. Each type of track had "narrow" or "wide" tracking guidelines. It was hypothesized that these guidelines would affect control strategy and in particular would affect ERRLIM, the HOPE representation of an internal performance standard. The logic behind this hypothesis is as follows.

Task performance is often influenced by externally provided standards for performance. Disregarding very high or very low standards, performance is more likely to be of high quality when external standards for performance are moderately high. It is proposed that this effect is mediated by internal performance standards. Such standards are, in part, subjectively determined, but also are responsive to, and change with, external standards. The internal standard influences the quality of performance by limiting excessive error, and is one aspect of the control strategy used to guide performance. ERRLIM is HOPE's representation of an internal performance standard. If these previously discussed assumptions are correct, then the ERRLIM of HOPE models which best predict human behavior should vary with external standards for

performance, such as track guidelines. This hypothesis can be examined by comparing the ERRLIM values of the best fit models for performance in conditions of wide versus narrow guidelines.

The guidelines might also be expected to have a second effect on control strategy. Subjects viewing a track with wider, more generous guidelines might be less hesitant to make bold control movements in the face of excessive error than subjects who view narrower, more restrictive guidelines. If such were the case, then ADJUST values in HOPE models which best predict human behavior in wide guideline conditions should be larger than ADJUST values for models which best predict behavior of subjects in narrow guidelines.

In summary, if HOPE is valid, control strategy, as inferred from CSP values of best fit models, should vary between different training conditions. In the present experiment it seems likely that COT should be particularly sensitive to differences in track frequency, ERRLIM should be sensitive to differences in track guidelines, and ADJUST should vary with both.

It is important to note that if the conceptualization of control strategy is valid, differences in control strategy may not be immediately apparent but should emerge during the course of learning. As was discussed with reference to Question 2, initial control strategies, although often related to past experience, are likely to be relatively ineffective in performance of a new task. In the present experiments using inexperienced subjects, it is unlikely that there are systematic differences in the control strategies used initially by subjects in the four different training conditions. However, if the conceptualization of control strategy is correct, differences in the control strategies used in the different training conditions should emerge over the course of learning, with more clear-cut differences emerging on the later trials. For these reasons, special attention will be focused on the CSP values of the best fit models for behavior in the first and fifth trial of the four different training conditions.

B. Method

1. Design

A 2 x 2 between-subjects design was used with track frequency (¼ Hz or ½ Hz) as one independent variable, and guideline width (narrow or wide) as the second independent variable.

Thus, the four experimental conditions were:

¼ Hz track, narrow guidelines
¼ Hz track, wide guidelines
½ Hz track, narrow guidelines
½ Hz track, wide guidelines.

2. Subjects

Subjects were 16 men and 16 women, all paid volunteers from ROTC units. Eight subjects were assigned to each condition, with equal numbers of men and women in each condition.

3. Apparatus

The apparatus is displayed in Figure 19. The track and guidelines were presented on a Grinnell Systems GMR-27 digitally refreshed graphics display. The Conrac video monitor was 37.38 cm wide by 26.06 cm high. The track was generated by passing a pseudo-random signal through a low-pass filter. The track generation procedure is detailed in Appendix B. The track traveled downward from the top of the screen. About five seconds of track preview were available during tracking. The guidelines were centered around the track. Narrow guidelines appeared $\pm$ 1.6 cm directly horizontal of the track; wide guidelines appeared $\pm$ 3.58 cm directly horizontal of the track. Figures 19 to 22 show the tracks as they appeared in each of the four conditions.

The subject controlled a cursor in the form of a small plus (+) visible on the screen. The cursor moved only in the horizontal dimension halfway between the top and bottom of the video screen. Control was by means of a low friction isotonic stick with seven bits of position output, or 128 possible positions ($2^7 = 128$).

To minimize effects of past experience, the relationship between stick and cursor position, or control dynamics, was position type with non-linear first order lag. The cursor was more responsive to stick movement when the stick moved in the middle of its range than at extremes. Learning these control dynamics was the fundamental learning task for the subjects and for the models. Appendix C contains details of the control dynamics.

An Interdata Corporation mini-computer recorded control stick position every 40 msec. This same computer was used for data analysis.

4. Procedure

Subjects were seated at a desk from which protruded the control stick and the key used to start each trial. About 1 m in front of them was the display screen. Subjects in all conditions were given the following instructions, which are fully consistent with the procedure used:

"The experiment you are participating in today involves using a control stick to control a cross-hair on this CRT screen. You are to control the cross-hair so as to stay as close as possible to the center line of a moving track you will see displayed in front of you. You will have five 4-minute periods to learn this task, with a one minute break in between each. The track will move down the screen from the top. The cursor you control is able to move only in the horizontal

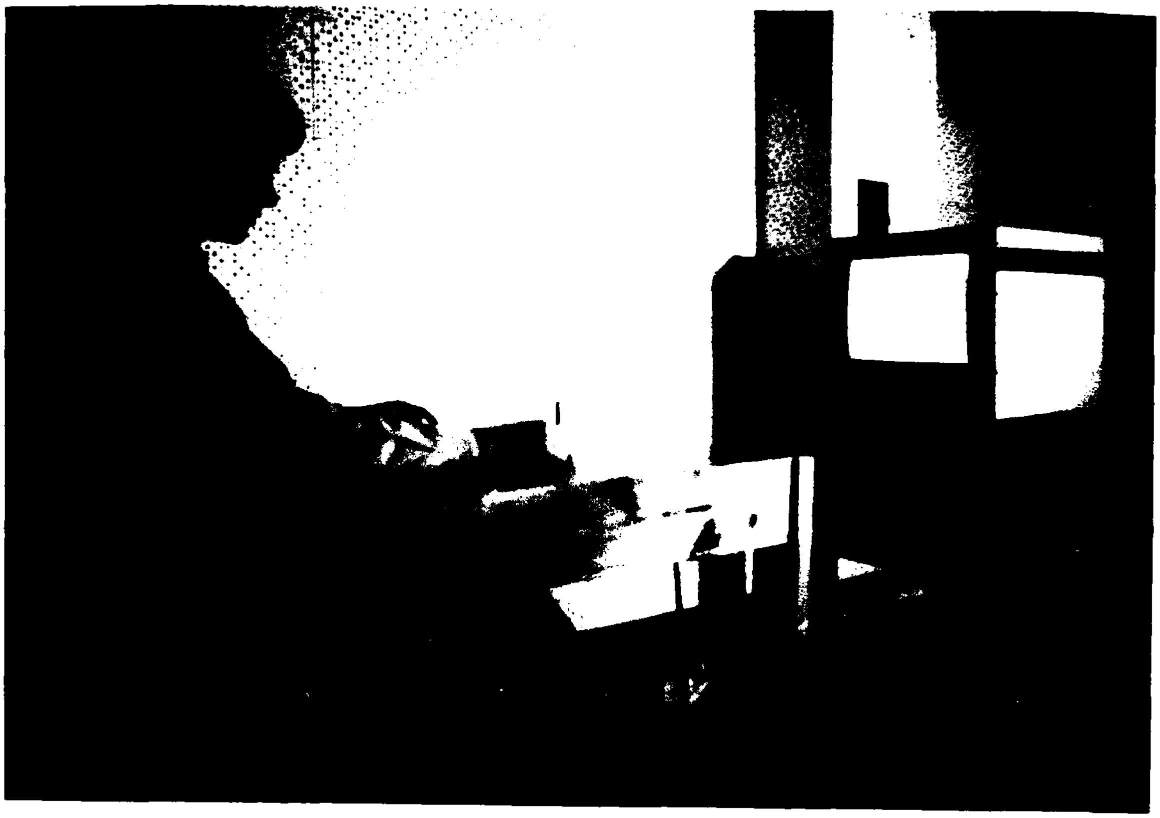

Figure 18. Apparatus used in preliminary testing of HOPE.

Figure 19. Track in 1/4 Hz, narrow guideline condition.

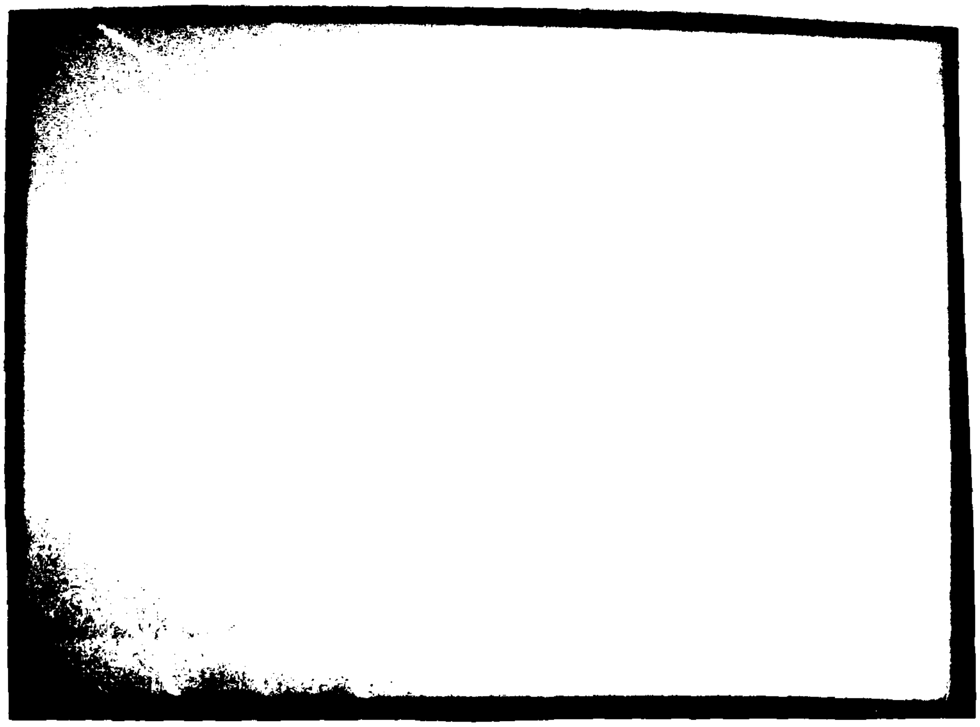

Figure [illegible] Track in 1/4 Hz, wide guideline condition.

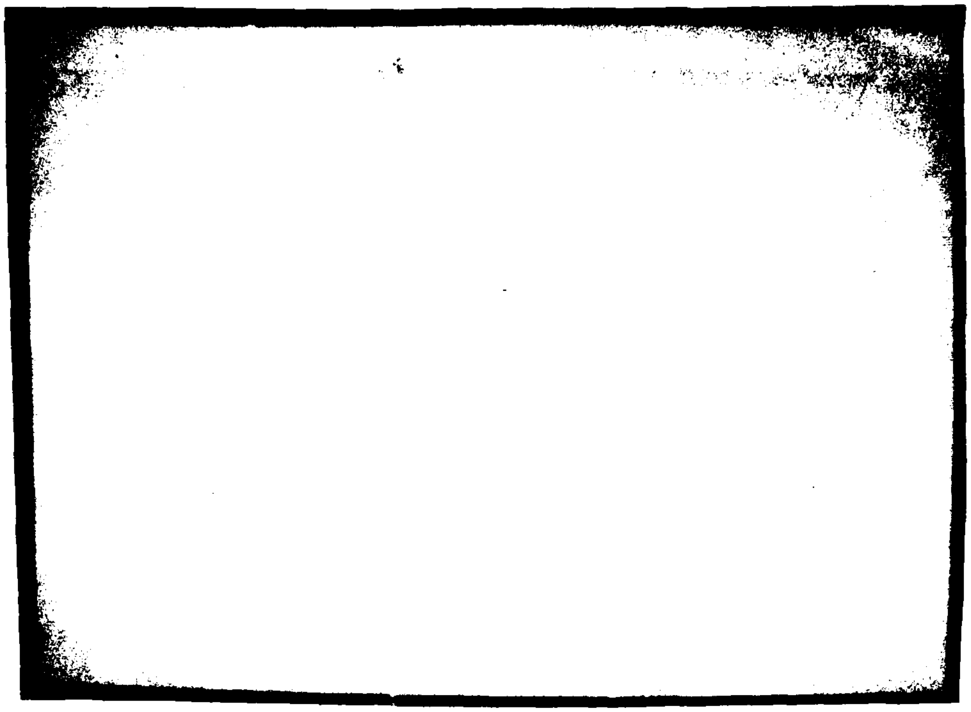

Figure 21. Track in 1/2 Hz, narrow guideline condition.

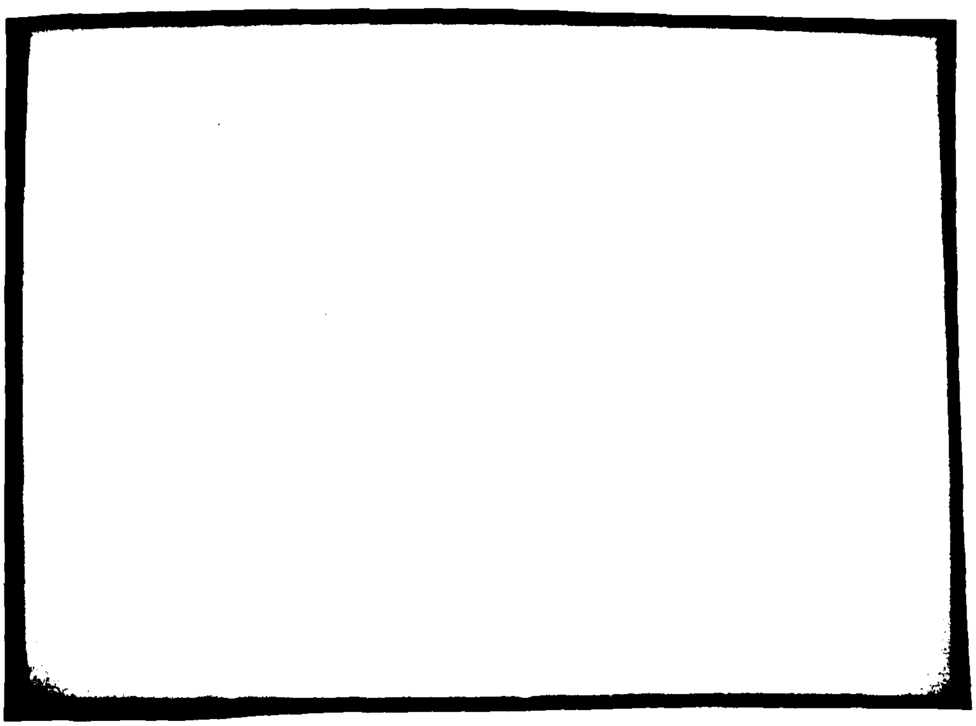

Figure 22. Track in 1/2 Hz, wide guideline condition.

direction and will be located at the middle of the screen. You will see guidelines displayed on each side of the track to help you track accurately. After each trial, wait one minute, and then push the button on the table to start the track again.

"Now I'd like you to get familiar with the positions available on this stick. Take hold of the stick and move it around until you think you're sure about where the center is, and where other positions on the handle are.

"The cursor-control stick 'machine' is different from any you have ever experienced. You may find it difficult to control at first, but it will get easier very shortly. At all times try to keep the cursor as close as possible to the center of the track. The four men and the four women who track most accurately overall will receive an additional $5, as well as the $10 participation fee. Try to do the best you can. Remember, after each trial, wait one minute and push the button to bring on the next trial.

"Do you have any questions about the task you have to do?

"Now begin."

After each test session, subjects were given a brief explanation of the project, as follows:

"We have a theory about how people learn to control vehicles such as cars and airplanes, or even how to hit a tennis ball properly. We believe you build up a special memory for the consequences of everything you do, and when you get back into the same, or a similar situation, you repeat actions that have been successful.

"We have taken our theory, which is quite elaborate, and created a computer program which does part of what we believe all humans do when they learn a control task. We call the computer program HOPE, an acronym for Human Operator Performance Emulator. We will take the recorded output from your control stick actions, and find the controlling parameter set which allows the HOPE output to best match your output for each 20 second interval in your tracking record. Then we will look at the values of the controlling parameters in the HOPE model of you in the hope of learning something about psychological processes involved in learning this task.

"Do you have any questions?"

5. <u>Data Analysis Plan</u>

a. <u>Choice of best-fitting HOPE models</u> - Each subject's control stick output was divided into sixty time bins of 20 seconds each (5 track repetitions x 4 min each)/20 sec = 60 time bins, with 12 time bins per track repetition). Since data had been recorded every 40 msec

during testing, there were 500 data points per time bin (20 sec/40 msec = 500).

For each time bin, a comparison was made between human control stick positions and the control stick positions for that time bin predicted by each of the 75 HOPE models. A best-fit model for each time bin was selected.

The procedure for selecting the HOPE model which best-fit human output for each time bin involved computing a measure of the difference between human output and the predictions of each of the 75 HOPE models, and then ranking the goodness of the models according to their difference from human output. The end result was, for each time bin, a ranking of the 75 models in terms of how well each predicted a subject's control stick output in that time bin.

Two different statistics for describing the difference between human behavior and model behavior were investigated: root mean square error (RMS) and mean absolute state error (MASE). RMS error is a conventional measure used for describing the difference between two waveforms, but it has the disadvantage that it considers mainly position difference between model and human output in describing the difference between them. MASE is a newly developed statistic which includes information about position, velocity, and acceleration differences to describe the overall difference. MASE is computed as the sum of: a) the absolute values of the instantaneous differences between positions, b) the first derivative of position difference (velocity), and c) the second derivative of position difference (acceleration).

Appendix D provides details of the computation of MASE, and procedures used in an initial attempt to validate MASE. For a test bin, MASE rankings and RMS error rankings of the ten best models were compared to human rankings. Although both measures agreed somewhat with human choices, MASE choices agreed no better than RMS error choices with human judgements. In view of the novelty of MASE, and the fact that RMS error has been applied usefully many times before, it was decided that RMS error should be used to judge human-model behavior fits for this report. However, since MASE does employ more information in describing differences and is computationally simpler, future work should be devoted to further development of MASE.

The RMS error calculation was performed as follows. Human control stick position was recorded every 40 msec throughout the experiment. HOPE generated 75 model predictions of control stick positions for each of the four training conditions. For each model in a given task condition, the position differences between model and human control stick position for each 40 msec measurement point were squared and summed within each 20 sec time bin. RMS error was the square root of the sum. For each time bin, models were ranked as to their goodness of fit with human behavior according to their RMS error value. The model having the smallest RMS error value was chosen as the best match model.

b. Development of subject learning curves - Learning curves for each subject were developed using mean absolute position error. The difference between cursor and track position was computed for each 40 msec measurement point and was averaged within each 20 sec time bin. The purpose of this analysis was to determine the point of performance asymptote, so that control strategy before and after asymptote could be compared.

c. Computation for each subject of average values for control strategy parameters of best-fit models for each trial - These data were used in an analysis of variance due to training conditions.

d. Preparation of matrices of control strategy parameter values for best-fit models for each time bin - For each subject, two 2-dimensional matrices were prepared. One matrix listed for each of the 60 time bins, the ten best model fits in order of goodness. The second matrix listed for each of the 60 time bins, the CSP values of the ten best model fits. This data was used to examine the clustering of the CSPs of the ten best-fit models in order to propose model refinements. Appendix E shows a sample of this data.

C. Results and Discussion

In this section, answers to the questions presented in Section VA which formed the basis for the design of the preliminary tests are discussed, along with the evidence on which those answers are based.

Question 1: Do HOPE models match human behavior to an acceptable extent?

It was earlier stated that the criterion for acceptable matching would be met if for 90% of the subjects, HOPE models matched human behavior within a boundary of 20% of the control stick's range of motion for at least half the duration of testing. This criterion requires that the RMS difference value be less than 7.5 cm for the best-match models of at least 30 time bins for each subject.

HOPE models matched human behavior well within this criterion. For each subject in the ¼ Hz condition, at least 59 out of the 60 time bins of tracking were matched by models within the criterion RMS difference score. For the ½ Hz condition 15 of the 16 subjects were matched within the criterion. Twelve out of the sixteen subjects met the RMS difference criterion on 50 or more time bins. Given that the criterion selected was somewhat arbitrary, it is important to note that HOPE's matching of human behavior would have been acceptable even with the use of a stricter criterion, either in terms of number of time bins to be matched, RMS difference values, or number of subjects to be matched.

In summary, HOPE models did match human behavior to an acceptable extent. However, the pattern of the quality of the matching over trials

and between the two track frequency conditions raises several interesting questions. Table 2 shows for each subject the average RMS difference value for best match models for each trial. Figure 24 to 25 show plots of human and best fit model control stick positions for certain representative subjects. These data indicate that model matching was better for behavior in the ¼ Hz condition and for behavior later in training.

One question is why HOPE was able to generate control stick positions which better matched the ¼ Hz track condition. For both the ½ Hz and ¼ Hz tracks, HOPE models generated control stick positions with position errors low and at least equivalent to that of human control stick positions. Yet these ½ Hz models were not the best match for human behavior, as judged by minimal RMS error values. The current conceptualization of HOPE and control strategy does not predict better matching of ¼ Hz track behavior.

A second question is why model behavior matched human behavior better as training progressed. If the present HOPE simulation is correct, then it should be able to generate control stick positions which match early and late training behavior equally well. This problem is especially intriguing because even though the models did not match humans as well on early trials, there were some models whose match to the track, in terms of position error, was as good as human performance on early trials. In other words, on each trial there were models that tracked as well as humans, but the match to human behavior was less good on early trials.

There are many possible explanations for these patterns in the quality of model-human matches. One possibility is that HOPE is not yet able to represent the control strategy used when tracking is relatively "more difficult," as it is early in learning, or when following a rapidly varying, ½ Hz track. The CSP values selected for this test might not be as adequate for describing the control strategy applied in these more "difficult" conditions. An expansion of the range or fineness (quantization) of CSP values may allow HOPE models to better emulate human performance in "difficult" conditions.

Secondly, it could be that some aspects of the learning or memory processes embodied in the simulation lack psychological validity. For example, HOPE begins training with a "blank" memory--no knowledge of control behavior. People probably begin with some knowledge of control tasks, even though they may never have experienced this particular nonlinear control task. The difference in beginning knowledge may result in the use of different control strategies by HOPE and by humans, thus producing a mismatch in their behavior early in training.

In summary, HOPE models do match human behavior to an acceptable extent, according to the criterion defined prior to testing. The matches tends to be better later in training, and for the ¼ Hz track condition.

TABLE 3

AVERAGE ROOT MEAN SQUARE DIFFERENCES (in cm) BETWEEN
SUBJECTS AND SAME-TRIAL BEST FIT MODEL CONTROL BEHAVIORS
FOR ALL TRIALS AND SUBJECTS

a. ¼ Hz Track, Narrow Guidelines

SUBJECT	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
1111	2.49	2.68	2.13	2.01	1.90
1112	2.46	2.35	2.16	2.26	2.00
1113	2.55	2.38	2.23	2.03	2.03
1114	2.45	2.41	2.09	2.09	1.99
1121	2.19	1.91	1.83	1.88	1.84
1122	2.47	2.19	2.11	2.13	2.16
1123	2.46	2.15	1.92	.238	1.93
1124	2.38	1.86	1.85	1.90	1.92

b. ¼ Hz Track, Wide Guidelines

SUBJECT	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
1211	2.01	1.78	1.67	1.58	1.53
1212	2.36	2.48	2.21	1.86	2.02
1213	2.22	1.79	1.85	1.75	1.69
1214	2.47	1.74	1.62	1.52	1.51
1221	2.26	1.97	1.76	1.79	1.75
1222	2.34	2.02	1.87	1.92	1.71
1223	1.95	1.62	1.65	1.60	1.58
1224	2.29	1.97	1.86	1.68	1.68

TABLE 3 (Concluded)

AVERAGE ROOT MEAN SQUARE DIFFERENCES (in cm) BETWEEN SUBJECTS AND SAME-TRIAL BEST FIT MODEL CONTROL BEHAVIORS FOR ALL TRIALS AND SUBJECTS

c. ½ Hz Track, Narrow Guidelines

SUBJECT	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
2111	8.51	7.64	7.84	7.48	6.84
2112	6.07	6.39	6.10	6.52	6.09
2113	4.59	4.85	4.86	5.00	4.49
2114	7.98	7.18	7.47	6.18	6.42
2121	6.38	5.23	5.31	5.17	5.12
2122	6.95	7.86	6.16	6.22	6.76
2123	4.59	4.81	4.90	4.80	5.08
2124	4.68	4.81	5.01	4.69	4.60

d. ½ Hz Track, Wide Guidelines

SUBJECT	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
2211	6.41	4.93	4.69	4.61	4.40
2212	5.60	6.20	5.54	5.48	5.54
2213	4.01	3.87	4.25	3.92	4.93
2214	6.05	5.42	4.25	4.47	3.68
2221	5.03	4.82	5.36	5.39	4.34
2222	4.19	3.22	3.32	3.61	3.90
2223	4.81	4.25	3.90	3.90	3.80
2224	4.04	5.03	5.41	5.67	5.51

	Mean Absolute Position Error (cm)		Best Fit Models Control Strategy Parameters			
	Human	Model	COT	ERRLIM	ADJUST	RMS Error(cm
Bin 55	.600	.584	5	5	2	1.79
Bin 56	.753	.686	5	5	2	1.93

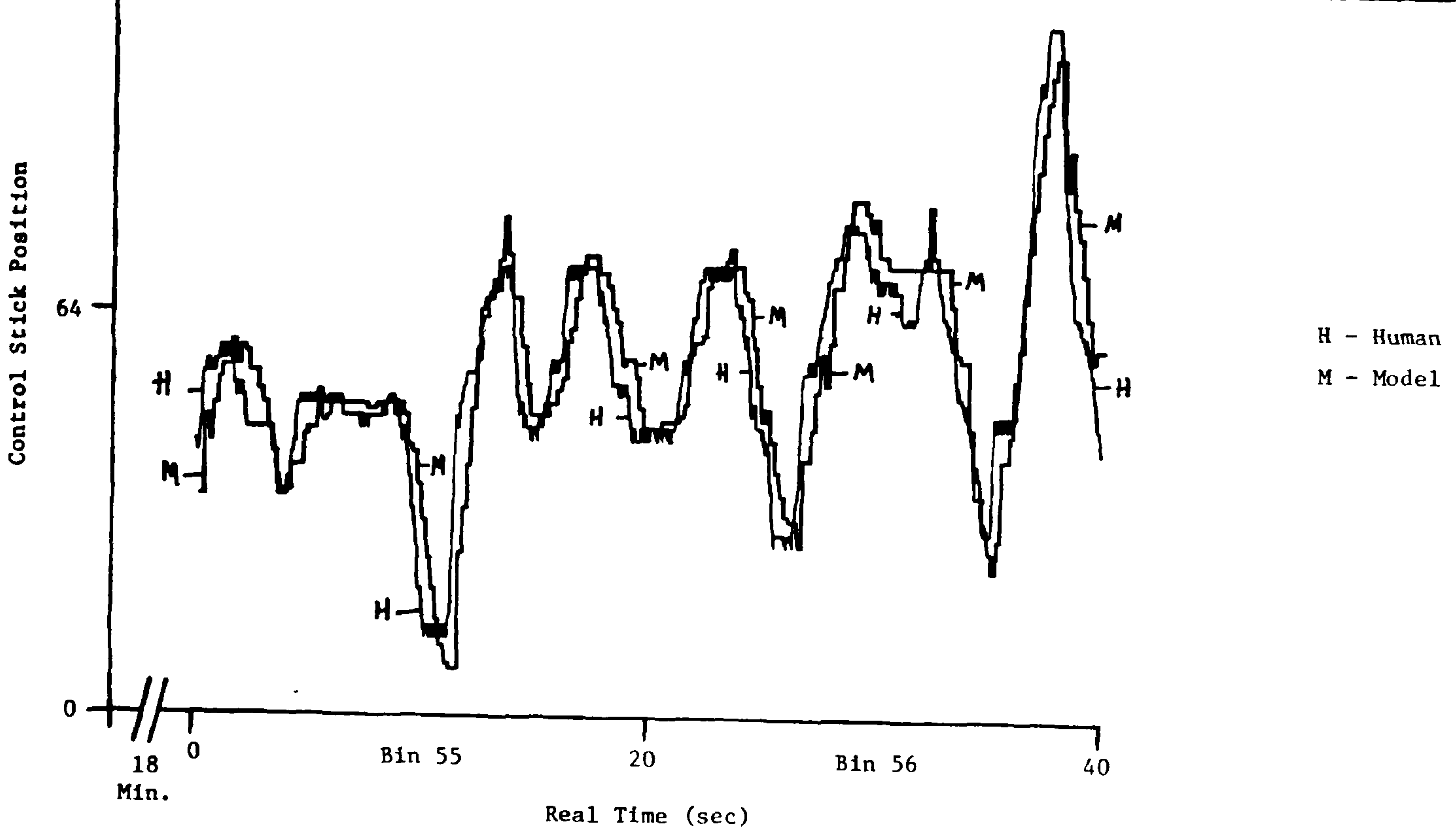

Figure 23 Example of Control Stick Positions of Subject 1212 and Best-Fit Models (Tracking 1/4 Hz Track; Non-linear First-order Plant).

	Mean Absolute Position Error (cm)		Best Fit Models Control Strategy Parameters			RMS Error (cm)
	Human	Model	COT	ERRLIM	ADJUST	
Bin 53	.846	.975	2	16	5	3.47
Bin 54	.784	.863	2	32	8	3.94

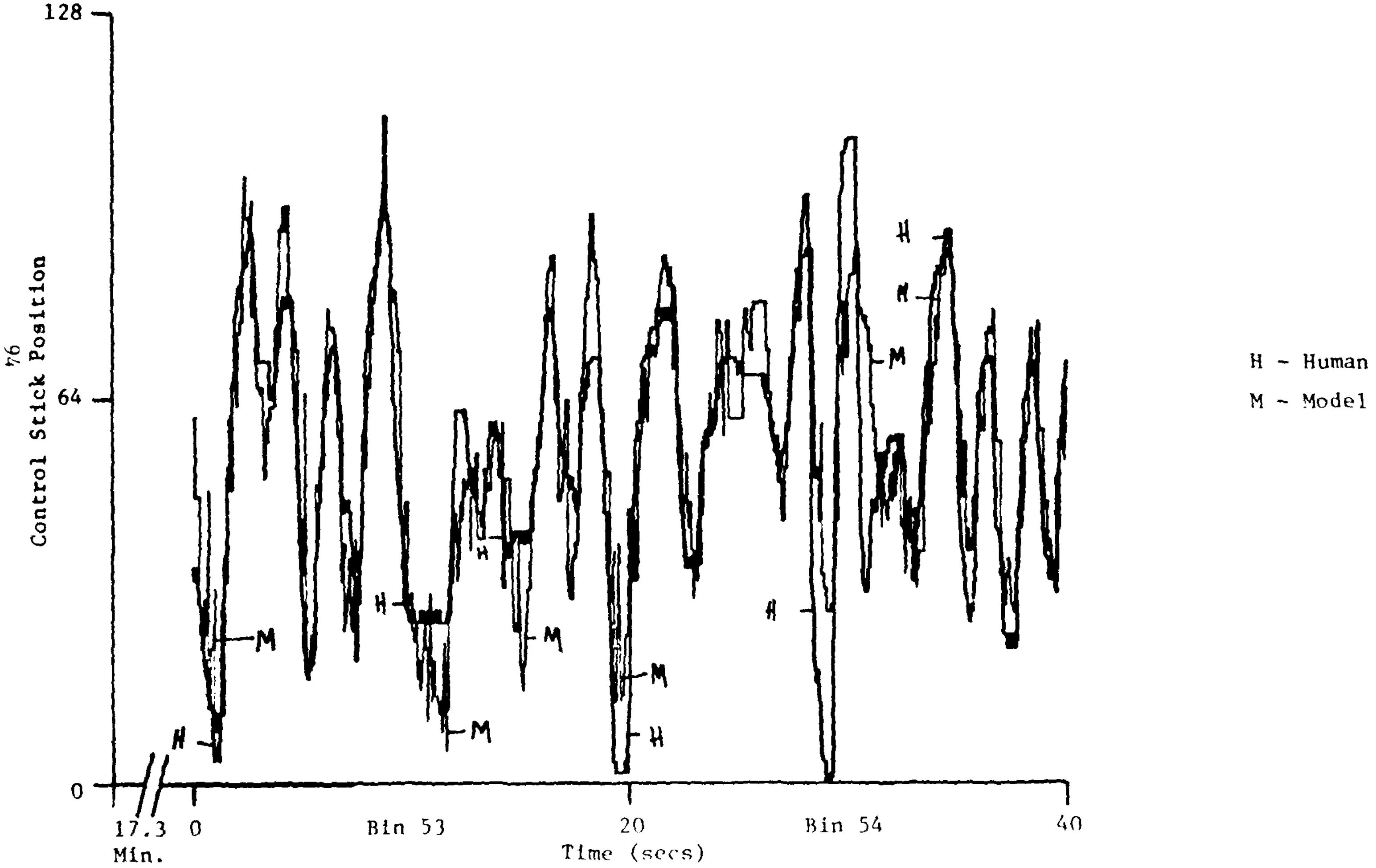

Figure 24. Example of Control Stick Positions of Subject 2222 and Best-Fit Models (Tracking 1/2 Hz Track; Non-linear First-order Plant)

Question 2: Does control strategy, as identified by HOPE, vary over the course of learning?

An essential prerequisite for answering this question is evidence that the subjects did learn to track more accurately over trials. If humans did not learn, then changes in control strategy as identified by HOPE would not be predicted. Figure 25 shows the mean absolute position error for humans for each condition for each trial. It is clear that human learning did occur, in that position error decreased over trials in all conditions. Position error was significantly less on Trial 5 than on Trial 1 ($F(1,28) = 29.63$, $p < .001$). It is not clear whether learning reached an asymptote within the period of training used in this test.

The next issue is whether the control strategy, as measured by HOPE models, changed with learning. This issue was examined by looking at the differences in mean CSP values of best fit models for Trial 1 versus Trial 5. For each parameter, the difference between the mean Trial 5 value and the mean Trial 1 value was computed.

To analyze whether overall control strategy changed, a multivariate analysis of variance was performed[1], with the three CSP Trial 5 minus Trial 1 difference scores as dependent variables. The three-dimensional vector representing control strategy change was significantly different from zero ($F(1,28) = 217.30$, $p < .001$) indicating that control strategy did change between Trials 1 and 5.[2]

Univariate analyses of variance were also performed on the Trial 5 minus Trial 1 difference scores for each CSP. For command operative time (COT), this difference score was significantly different from zero ($F(1,28) = 561.66$, $p < .001$). Figure 26 shows the change in COT value over trials for each condition. The largest Trial 1 minus Trial 5 COT differences appear to be in the ½ Hz conditions, an idea which is supported by the fact that the difference score varies significantly between track frequency conditions ($F(1,28) = 100.04$, $p < .001$). This fact will be important in upcoming discussion of Question 3.

[1]Multivariate and univariate analyses of variance were performed using the program MANOVA, created by Eliot Cramer of the Psychometric Laboratory at the University of North Carolina.

[2]One alternative approach to the analysis would have been to use the method of orthogonal polynomials to test the form of the trial to trial changes, testing for linear, quadratic, or cubic trends. This approach seemed inappropriate for this preliminary study. Measures of control strategy are quite unrefined, and such an analysis of the form of changes over time was believed to require more measurement precision than presently exists.

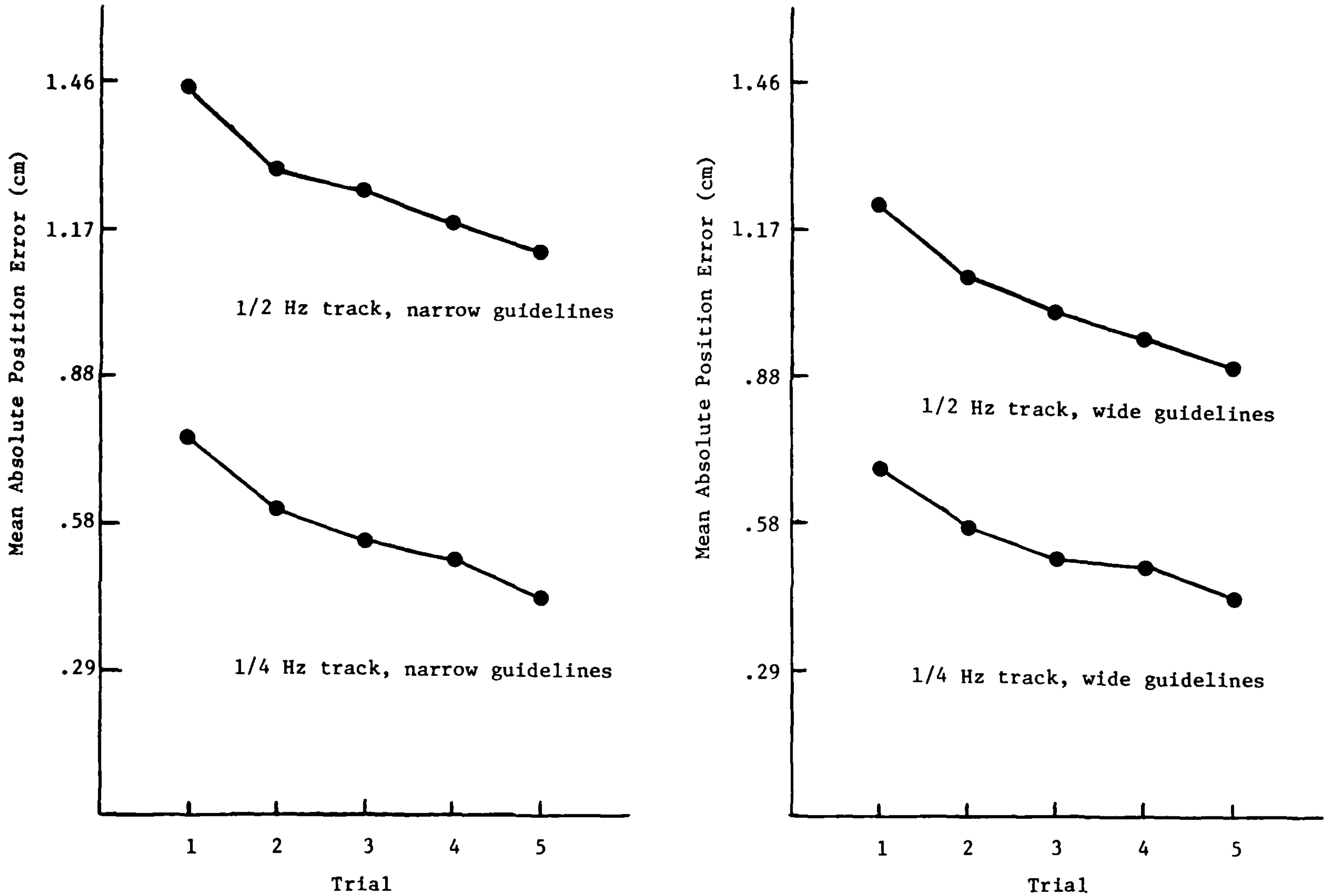

Figure 25. Mean Absolute Position Error as a Function of Trials and Conditions

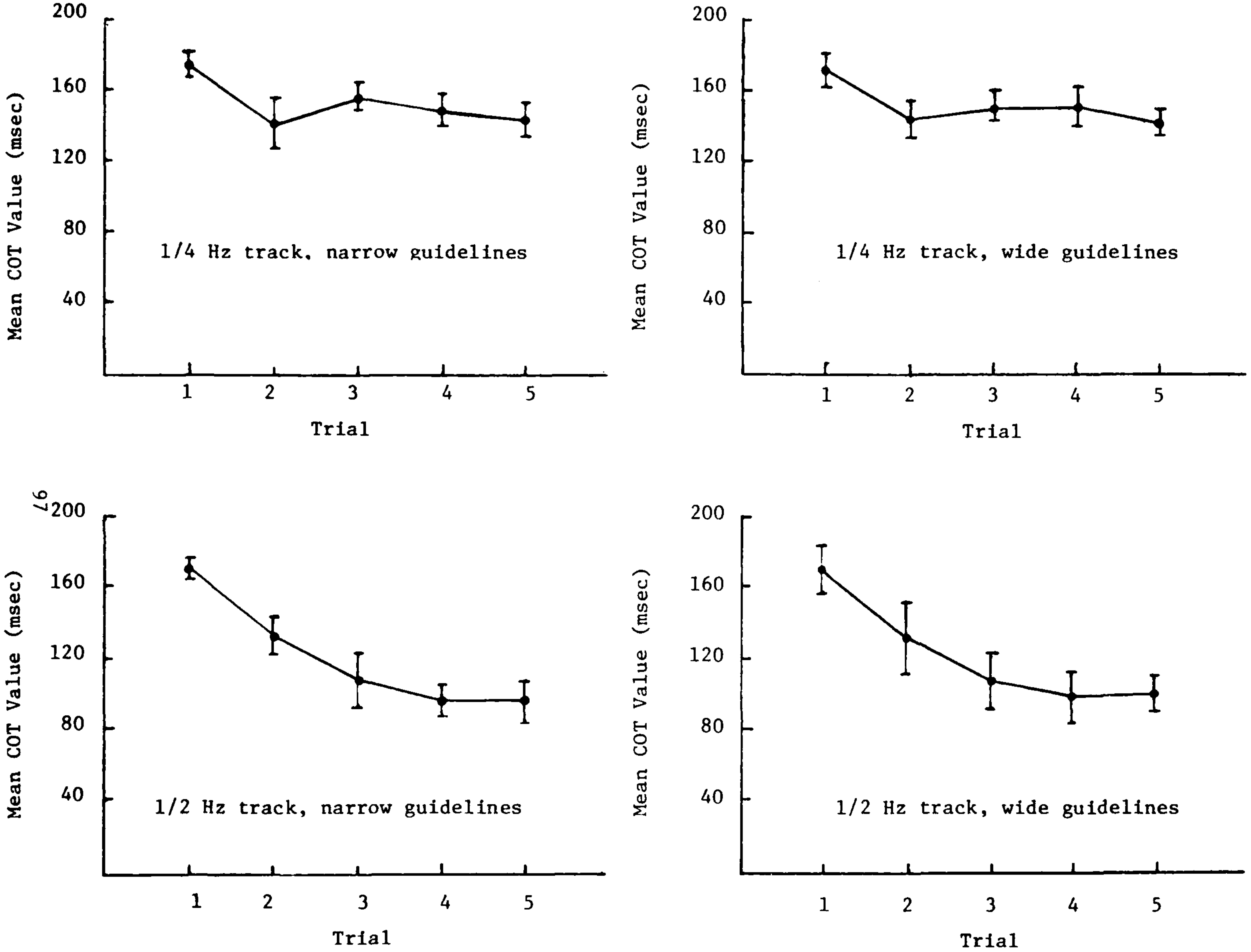

Figure 26. Mean COT Values as a Function of Trials and Condition.
(with points bracketed by one standard deviation)

ERRLIM also differed significantly between Trial 1 and 5 ($F(1,28) = 165.32$, $p < .001$). Figure 27 shows the changes in ERRLIM over trials for each condition. Greater changes in ERRLIM occurred in the ½ Hz than in ¼ Hz track conditions ($F(1,28) = 880.00$, $p < .001$) and with narrow guidelines than with wide guidelines ($F(1,28) = 8.44$, $p < .007$).

The trial one minus trial five ADJUST change was also significantly different from zero ($F(1,28) = 101.26$, $p < .001$). As can be seen in Figure 28, ADJUST changed more in the ½ Hz conditions than in the ¼ Hz conditions. Overall, there was a tendency for ADJUST means to be clustered near the minimal values currently tested. It is possible that a larger and more consistent Trial 1 minus Trial 5 ADJUST difference might be observed if the possible ADJUST values in HOPE were expanded in the lower range.

In summary, control strategy did differ significantly between Trial 1 and Trial 5. The amount of change for particular control strategy parameters tended to vary as a function of training conditions. This point will be discussed further in analysis of data relevant to Question 3.

Question 3: Does control strategy, as identified by HOPE, reflect differences between training conditions?

Earlier discussion pointed out that during the course of learning, individuals develop control strategies appropriate to the current training condition. Since it takes time for a task-appropriate control strategy to develop, control strategy may not vary with training condition early in learning. However, more extended practice allows time for the development of task-specific control strategies appropriate for different conditions.

To examine these hypotheses, the CSPs of best fit models for behavior in different training conditions were compared. The above discussion implies that there should be no significant differences in CSPs early in training, but there should be differences later in learning. The CSPs of best fit models for Trial 1 and for Trial 5 were analyzed for variations between conditions.

As can be seen in Figures 26 to 28, for each CSP, the values on Trial 1 did not vary very much between training conditions. This would be expected if subjects begin training using relatively unsystematic control strategies. These observations are supported by the outcomes of a multivariate analysis of variance with the three control strategy parameters as dependent variables. On Trial 1, the three dimensional vector representing control strategy did not vary significantly between training conditions ($p > .05$). None of the univariate analyses of the CSPs revealed differences between values on Trial 1.

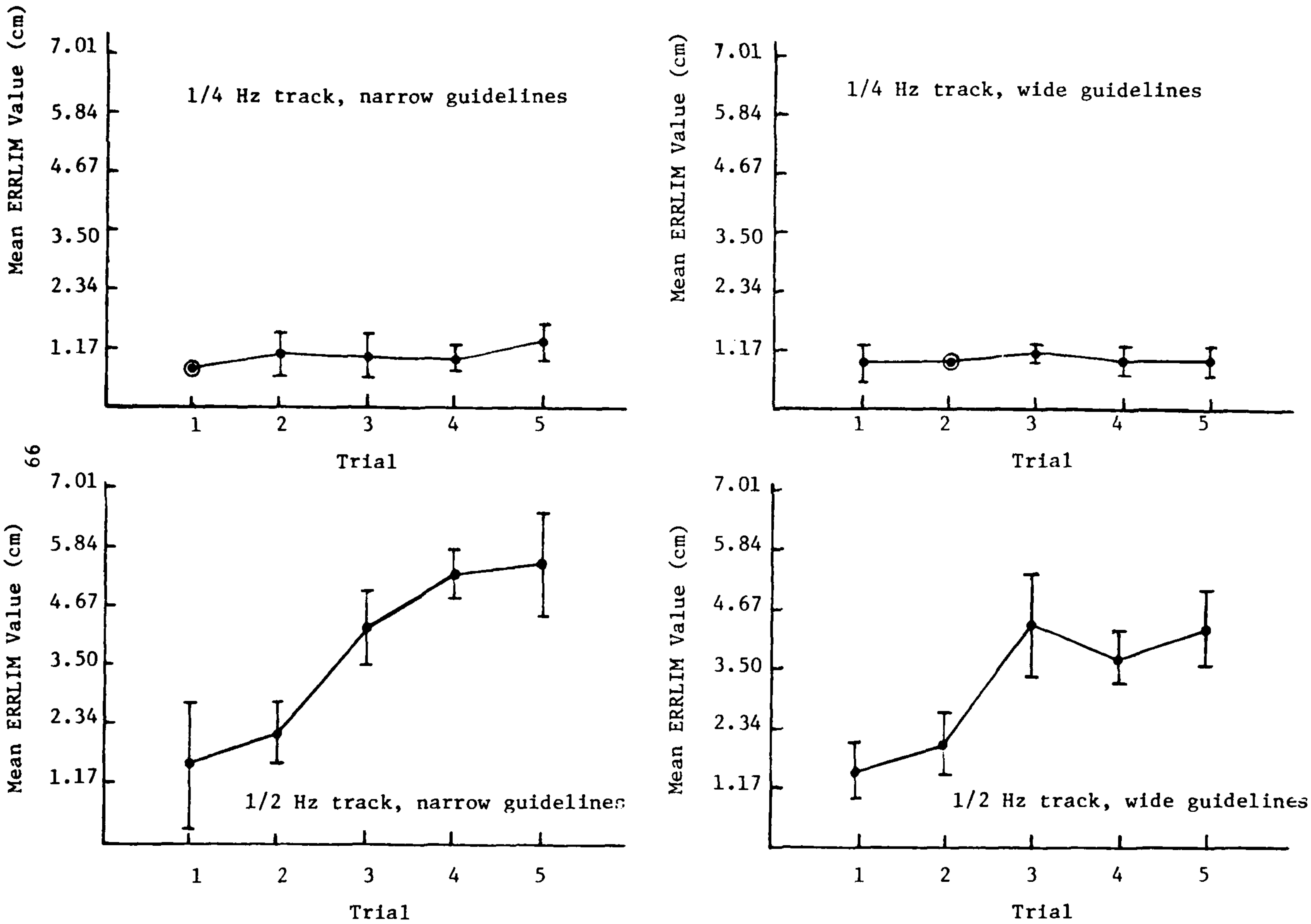

Figure 27. Mean ERRLIM Values as a Function of Trials and Conditions.

(with points bracketed by one standard deviation)

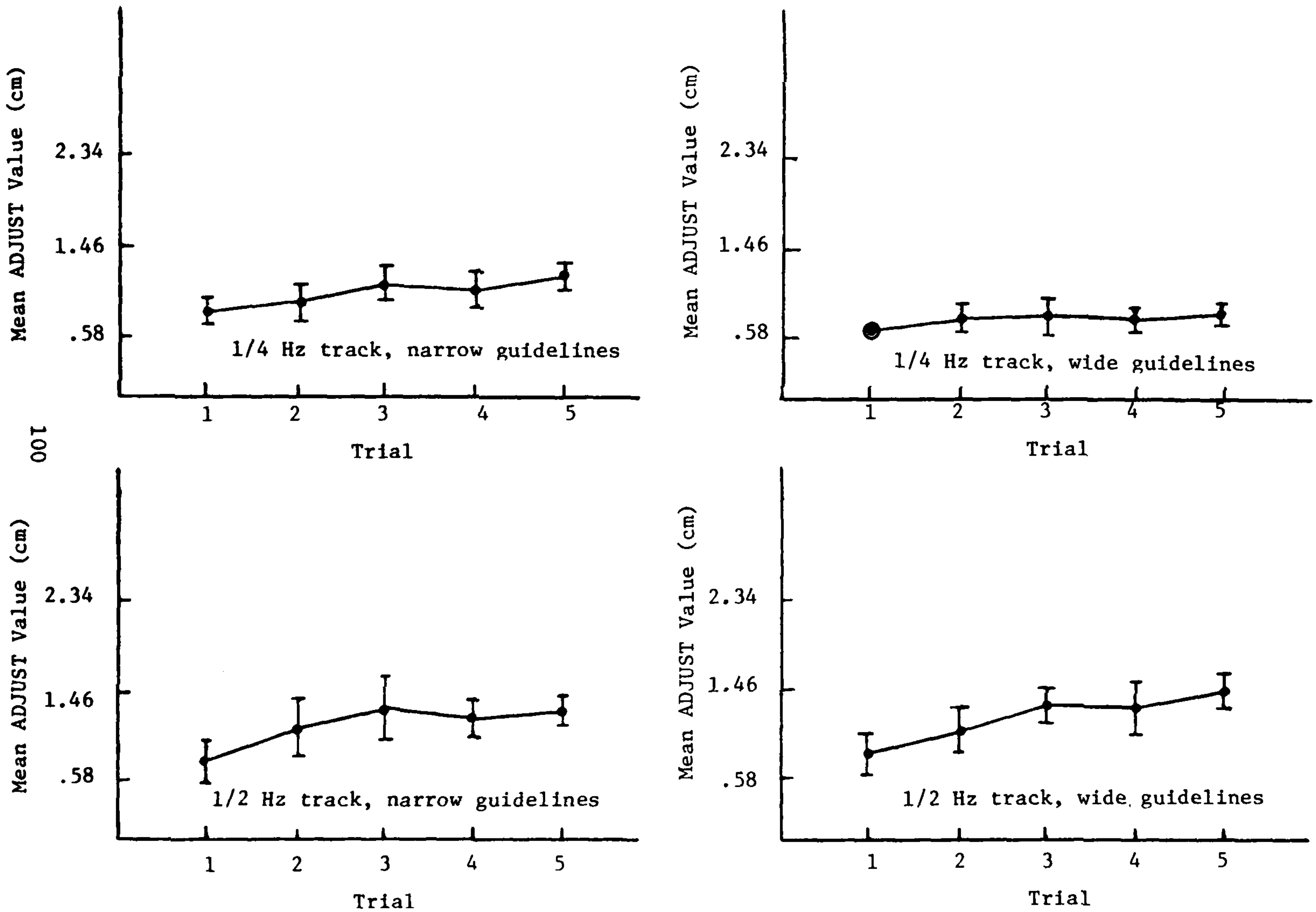

Figure 28. Mean ADJUST Values as a Function of Trials and Conditions.
(with points bracketed by one standard deviation)

In contrast, on Trial 5, there is considerable variation in CSP values between training conditions (see Figures 27 to 29). The three dimensional vector representing control strategy varied significantly between conditions ($F = 7.70$, p .001. Univariate analyses indicated that on Trial 5 ERRLIM varied significantly between guideline conditions ($F(1,28) = 10.27$, p .003), though other CSPs were unaffected by guidelines. Differences in track frequency were reflected in differences in COT ($F(1,28) = 144.60$, p .001), ERRLIM ($F(1,28) = 223.39$, p .001) and ADJUST ($F(1,28) = 38.78$, p .001).

These patterns in the data support HOPE's representation of control strategy. Control strategy as measured by HOPE did not vary between training conditions early in learning, when human control strategy would not be expected to be task-specific but did vary later in learning, when task specific control strategies should have been developed by subjects.

Earlier discussion also made predictions about the pattern of estimated control strategies that might be associated with different training conditions. As is shown in Figure 27, the Command Operative Time used later in learning was shorter for ½ Hz tracking conditions than for ¼ Hz tracking conditions. This difference developed over the course of learning. Although COT is shorter on Trial 5 than on Trial 1 for both track frequency conditions, there was a greater change in COT values for the ½ Hz conditions, as was pointed out in earlier discussion of data relevant to Question 2. Indeed, by the last trial, estimates of COT for subjects in the ½ Hz condition were just about half as long as for subjects in ¼ Hz conditions.

It was predicted that guidelines , representing external performance standards, would be expected to affect ERRLIM, representing an internal performance standard. Although ERRLIM did vary between guideline conditions on Trial 5, the pattern of the differences is somewhat unexpected. First of all, one might expect that stricter external performance standards in the form of narrow guidelines might be mirrored in a stricter internal standard, in the form of a smaller ERRLIM. In fact, just the opposite effect can be observed in Figure 27 ERRLIM in Trial 5 was larger when guidelines were narrow.

Secondly, ERRLIM varied with track frequency, as well as with guidelines, the former effect not being initially predicted. On Trial 5 ERRLIM was larger for the ½ Hz track condition than for the ¼ Hz track condition. This effect is also opposite from what one might predict based on intuition. It seems logical that in more difficult task conditions (i.e., the ½ Hz track), one might impose an internal performance standard at least as strict as that used in easier conditions, to avoid increases in error. In fact, both ERRLIM and position error are greater in ½ Hz track conditions.

Thus it appears that one of the basic assumptions guiding the ERRLIM predictions is incorrect. To review, these assumptions are as follows:

a. People have internal standards for performance.
b. External performance standards influence internal standards.
c. Stricter external standards lead to stricter internal standards.
d. ERRLIM is associated with the internal standard.

The first two assumptions reflect common sense, and in fact, receive support from the data, since ERRLIM did vary significantly with guideline conditions. The fact that only ERRLIM, and neither of the other two CSPs, varied with guidelines supports the idea that ERRLIM is associated with an internal standard influenced by external standards. With reference to the third assumption there is some reason to believe that it may not be valid within the context of the present laboratory experiment.

First of all, subjects were told that the guidelines were present to "help" them, but it was not implied that they were standards for performance. Instructions emphasizing the role of the guidelines as a standard might have led to results more consistent with expected effects on an internal standard.

Secondly, it could be that when subjects received cues which were perceived as making their task relatively difficult (e.g., narrow guidelines), they reduced possible stress by relaxing internal standards for performance and sacrificing error. This interpretation is supported by the fact that absolute position error was consistently greater in narrow as opposed to wide guideline conditions, even when track frequency remained constant. Such a relaxation in performance standards might not occur in a situation where increased error was associated with danger or other more highly motivating increased costs of error. Such costs could be manipulated in experimental tests including more highly motivating monetary incentives than those used in the present experiment. If ERRLIM does represent an internal performance standard, increased costs for increased error should be inversely related to ERRLIM value. Also, ERRLIM should become more strict as external performance standards become more strict.

The third CSP, ADJUST, varied only with track frequency conditions. As can be seen in Figure 28, on Trial 5 ADJUST was larger for the $\frac{1}{2}$ Hz track. This pattern is logical, since larger movements are necessary in conditions in which the track is varying more rapidly. The larger the ADJUST values, the larger the movements used in conditions of excessive error. However, one might also expect larger movements to be used when guidelines are wider. Theoretically, when guidelines are wider, an internal performance standard is relaxed, and more error is tolerated. This encourages the execution of bolder, larger commands. However, in the present testing, ADJUST did not vary with guideline conditions, suggesting movements were no bolder with the wide guidelines.

The failure of ADJUST to vary with guidelines supports the earlier suggestion that subjects did not pay much attention to the guidelines. Increased emphasis on the guidelines might lead to variation in ADJUST, as well as ERRLIM.

D. Summary

This section describes the preliminary testing of HOPE, a computer simulation of continuous motor learning, including the effects of control strategy. Control strategy is represented by three variable control strategy parameters (CSPs), referred to as COT, ADJUST, and ERRLIM. The CSPs modulate HOPE's performance. Using different values of these CSPs, HOPE generates predictions of human tracking behavior. The CSP values used by HOPE when it best matches human behavior were used to identify human control strategy.

In the preliminary testing human operators performed a preview tracking task in one of four training conditions: ¼ Hz track, narrow guidelines; ¼ Hz track, wide guidelines; ½ Hz track, narrow guidelines; ½ Hz track, wide guidelines. An attempt was made to provide preliminary validation and demonstration of HOPE by addressing the following three questions:

1. Does HOPE match human behavior to an acceptable extent?

2. Does control strategy, as identified by HOPE, change with learning?

3. Does control strategy, as identified by HOPE, reflect differences between training conditions?

HOPE models did match human behavior to an acceptable extent, with the matches being better late, rather than early, in training, and in the ¼ Hz, rather than ½ Hz, condition. Refinements of psychological representations in the model, and of the values of the control strategy parameters tested, may reduce these differences.

Control strategy, as identified by HOPE, did change with learning. For each CSP, the difference in value between Trial 1 and Trial 5 was significant. This change supports the assumption that control strategy varies over the course of psychomotor learning.

Finally, control strategy, as measured by HOPE, reflected differences between training conditions. If a task-appropriate control strategy develops during learning, then differences in control strategy should be more pronounced later in learning. This assumption is confirmed by the data. On Trial 1 there were no CSP differences in best-fit models between training conditions. However, on Trial 5, there were significant differences. In comparing ½ Hz and ¼ Hz track conditions, COT was shorter and ADJUST larger for the ½ Hz track. These differences seem consistent with the need for more quickly varying, bolder movements

in response to the faster track. ERRLIM was responsive to both guideline and track frequency conditions, being larger when guidelines were narrow or the track was faster. These effects are somewhat inconsistent with initial predictions. However, it may be that in the present laboratory conditions, subjects relaxed internal performance standards to minimize stress induced by more difficult conditions of tracking (i.e., narrow guidelines or ½ Hz track were the conditions associated with significantly larger error).

In summary, the preliminary testing of HOPE provides support for current assumptions about control strategy, and for the validity of using a computer simulation of strategy-controlled psychomotor learning to measure human control strategy.

SECTION VI

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. Summary of a Theory of Manual Control Learning and Performance

The present work provides preliminary evidence that it is possible to measure human control strategy through use of a psychologically-based computer simulation. The simulation is based on a theory of manual control behavior (see Section III) which includes assumptions about the following topics.

1. Mental Processes Important to Continuous Manual Control Learning and Performance

These mental processes include both decision-making and automatic processes. Decision-making processes take attention, and most likely are performed in a serial fashion. These include performance evaluation, association and storage of new task information, developing responses to novel situations, developing responses in conditions of excessive error, determining when attention may be redirected to another set of decision-making processes, and developing a strategy for control.

Automatic processes take place with little or no attention, and may be performed in parallel with each other and with decision-making processes. Automatic processes include perception, selection of well-learned motor commands, maintaining selected motor commands in short term store, and execution of motor commands.

These processes are believed to be important in manual control learning and performance, and common to all individuals. The processes vary in their functioning, depending on the individual's control strategy.

2. Parameters Important in Continuous Manual Control Learning and Performance: Control Strategy

The mental processes important in manual control may vary widely in their functioning in different circumstances. Control strategy is a set of parameter values that determines the form of these processes, and thus has a profound effect on learning and performance. The parameter value set that comprises control strategy dictates the following:

a. criteria for performance in various aspects of the task;

b. stimulus cues on which learning and performance will be based;

c. the sequence in which decision-making processes will be performed.

3. Structures Important in Continuous Manual Control Learning and Performance - Internal Models

During manual control learning, knowledge is accumulated in three different memory organizations, each of which describes temporal relationships between important task-related events. The task controller model describes relationships between states of a controlled-element, and states of a control input. For example, in preview tracking, this model specifies the motor commands which intervene between particular pairs of cursor (i.e., controlled element) states. An input model stores information about sequences of experienced stimulus states. This model allows the operator to predict upcoming task demands. The input model thus permits the structuring of movements, and the monitoring of self-initiated movements in the absence of preview.

Finally, a neuromuscular model stores associations between central nervous system states and limb states. It represents the individual's knowledge of his neuromuscular dynamics - the motor outcome in relation to neural signals issued from the brain.

4. The Theory and Its Application to Training Design and Performance Measurement

These summarized ideas are integrated in an overall theory of continuous manual control learning and performance that has important implications for the design of training. It is assumed that two major aspects of such learning are development of the internal models and development of a control strategy. The development of the internal models occurs as a function of interactions between the task-related mental processes. The frequency with which different mental processes occur varies over the course of learning. In particular, decision-making processes predominate early in learning, leaving little attention available for other tasks. Training conditions can be designed to emphasize information relevant to accurate internal models, and can thus encourage internal model development.

The second aspect of manual control learning involves the development of a control strategy. The development of control strategy is a decision-making process which may not occur in the absence of attention to it. The individual's initial control strategy in a new task is in part a function of control strategies used in similar tasks, and may vary widely between individuals. Control strategy is believed to be variable and plastic, and can be influenced by training conditions. Training conditions can guide the individual toward development of an optimal control strategy - optimal in the sense that it permits performance which is of high quality with minimal attention, and that it transfers well to performance in other, specified tasks. It is assumed that it is possible to identify and measure optimal control strategies either through use of this research, or by other means. Such measurement can constitute a more precise and informative measurement system than any other presently used. A system of measurement

built around the theory of strategy-controlled learning presented here could permit design of cost-effective training devices and simulators, as well as provide valid predictions of operator performance transfer from one task or training environment to similar environments.

B. Features of the Simulation, HOPE

The theory, as applied to preview tracking behavior, was operationalized in the computer simulation named HOPE (Human Operator Performance Emulator). The processes modeled in HOPE include cognitive processes and control strategies used during psychomotor learning. These processes relate to perception, learning, retrieval from memory, response execution, and performance monitoring. HOPE is a limited capacity processor which can use a variety of strategies to guide performance. Experience with tracking is stored in a two-dimensional, permanent command memory which links pairs of track positions with the commands that intervene between them. In contrast to describing function models of tracking, HOPE is a simulation of how humans learn the characteristics of any controlled element dynamics, even non-linear dynamics, without algebraic representation of the controlled element.

An important assumption made in the development of HOPE is the assumption that control strategies guide psychomotor learning. Control strategy is represented in HOPE in terms of three variable value control strategy parameters (CSPs): ERRLIM, ADJUST and COT. These parameters dictate, respectively, the amount of error allowed before major error correction procedures are applied, the magnitude of adjustment in response to excessive error conditions, and the length of time over which one motor command is active. Different models of psychomotor behavior are portrayed by HOPE, each corresponding to a specific control strategy defined by a specific set of CSP values. The models for the preliminary testing were generated by forming all possible combinations of five values of ERRLIM, five values of COT, and three values of ADJUST for four test conditions.

C. Preliminary Testing and Results

The basic task for the validation testing was a one-dimensional preview tracking task. Human subjects used a low friction isotonic stick to control the position of a cursor, and specifically, to try to center the cursor on a track traveling on a screen before them. Subjects tracked for five trials in one of four training conditions: 1/4 Hz track, wide guidelines; 1/4 Hz track, narrow guidelines; 1/2 Hz track, wide guidelines; 1/2 Hz track, narrow guidelines. Subject behavior was recorded and matched against the predictions of HOPE models using varying CSP values in the comparable training condition for a given time interval. The CSP values of the HOPE model which best matched human behavior were used to infer the control strategy for that subject during that interval.

Three basic questions were asked in this preliminary testing:

1. Do HOPE models match human behavior to an acceptable extent?

2. Does control strategy, as identified by HOPE, vary over the course of learning?

3. Does control strategy as identified by HOPE, reflect differences between training conditions?

The results indicate that HOPE models matched human behavior to an acceptable extent, with better matches for performance late in training, and in the 1/4 Hz track conditions. Human control strategy as identified by HOPE reflected qualities control strategy is believed to have. It changed with learning, being significantly different between the first and last trials. More importantly, there were no systematic differences between the control strategies associated with different training conditions early in training, but there were systematic differences in control strategies associated with different training conditions once subjects became experienced. This pattern supports the idea that task-specific control strategies develop during training. The differences between control strategies were logically consistent with the demands of the training conditions. For example, COT, ADJUST and ERRLIM all were larger for the more rapidly varying 1/2 Hz track than for the 1/4 Hz track. These differences suggest that in the 1/2 Hz track conditions subjects executed commands more frequently, used bolder commands during error correction, and relaxed their internal performance standard. These behaviors are sensible, given a rapidly varying, perhaps more difficult, track. The only unexpected result was the pattern of ERRLIM variation between narrow and wide guideline conditions. ERRLIM, representing an internal performance standard, was larger when an external performance standard (narrow guidelines) cued use of a stricter internal standard (i.e., smaller ERRLIM). There are, however, a variety of results suggesting that in the present testing conditions the guidelines were not perceived by subjects as a valid external performance standard. ERRLIM did seem, however, to represent an internal performance standard, since estimated values were largest (most lenient) in the conditions which were most difficult to perform.

D. Research Problems and Known Model Limitations

The major difficulties experienced in the present investigation were associated with: a) attempting to develop a computer simulation of processes not precisely described in the psychological literature and b) deciding how to choose the best-fit model for human behavior. The psychological literature is not precise with respect to the operation or timing of processes associated with continuous psychomotor behavior. Considerable time was spent developing specific ideas which could be operationalized in the computer simulation. Some of these ideas, such as the representation of long term motor memory, are inno-

vative and deserving of further study in themselves. The choice of which HOPE model which best fit human performance during a specific time interval was also problematic, in that human choice of a best-fit model from visual inspection was somewhat different from choices made on the basis of the conventional measure, root mean square (RMS) position error, or a newly developed measure, mean absolute state error (MASE). After some testing, it was finally decided to use the conventional RMS error to gauge model fits to human behavior.

E. Conclusions and Recommendations

This investigation indicates that it is possible to develop a psychologically based computer simulation of strategy-controlled, manual control performance that can be used to identify human control strategy. Preliminary testing indicates that the present simulation, HOPE, has psychological validity, and has potential for high quality, informative measurement of human control learning.

The success of the present HOPE simulation suggests a variety of recommendations for further research. These recommendations are at three levels: recommendations for refining the present HOPE, recommendations for expanding HOPE, and recommendations for further research suggested by the theory.

1. Recommendations for HOPE Refinement

The first recommendation for refining HOPE involves determining how the HOPE simulation might be refined to produce even better matches to human behavior. Although HOPE matches human behavior to an acceptable extent in all of the training condition tested, matches tend to be worse in the 1/2 Hz track condition, and for early trials of tracking. Careful comparison of best-match model and human behavior in these conditions might reveal consistencies in the differences between them, which could be used to guide changes in the simulation.

Refinement of HOPE should also include testing some of its assumptions about human information processing. One fundamental assumption which deserves further examination is the organization of the permanent motor memory, the Command Memory. The Command Memory stores associations between specific controlled element and control input states. However, others have suggested that permanent motor memory contains "schema" (Schmidt, 1975) or motor programs (Keele, 1968). Studies could be designed to distinguish between these alternatives, and therefore to test the validity of the current representation of permanent motor memory.

After refinement, the revised simulation should be further validated, and tested not only for its utility in identifying control strategy, but also as an aid in building a predictive model of control strategy development.

2. Recommendations for HOPE Expansion

HOPE evolved from a broad theory of continuous control behavior. Recommendations for expanding HOPE focus on expanding the model to reflect more of the characteristics of the theory. The current HOPE inputs visual information, models performance of a single task and develops an internal model for the task controller in its permanent memory. An expanded version of HOPE would include supervisory and subsidiary processes associated with performance of other tasks, and would identify a plan allocating attention among tasks. The current unidimensional Command Memory could be made multidimensional, allowing input of information from several modalities and the execution of a variety of responses. HOPE could be expanded to model pursuit or compensatory tracking by including the development an input model.

3. Recommendations for Further Research

A third area of recommendations concerns aspects of the theory that have implications for the design of more cost-effective training programs. One topic deserving investigation involves the definition of optimal control strategies for various manual control skills, and of methods for training these strategies. We have defined optimal control strategy for a given task to be that which produces high quality performance with minimal attention, and which promotes good performance transfer to other similar tasks. What cues should be emphasized to the trainee at each state of learning? What internal criteria should be fostered for various aspects of the task? How can task-related mental processing be manipulated directly? What processing skills should be emphasized in training? These are important questions about control strategy and its learning which would require extensive experimentation.

Another research topic involves the design of procedures for aiding trainees to develop an internal model of the task controller. If the internal task controller model is organized as was proposed, then it is of importance to determine what sets of state-to-state transitions will result in the most accurate controlled-element model. For most complex skills, it is not feasible to provide training for all possible experiences. There is a need to define the subset of experiences that can be trained and used for accurate generalization, or "filling-in" of memory, on the part of trainees.

Another area which should be investigated, based on its importance and potential for training applications, is the means by which persons can be trained to develop accurate input models. For many skills of importance, the input that is tracked is self-generated, and the only continuous monitoring of performance possible is through comparison to the input model. The questions of how this model is most rapidly and effectively learned should be explicitly addressed.

In summary, the present investigation has demonstrated that it is possible to develop a psychologically based computer simulation of

strategy-controlled behavior that can be applied to performance measurement. This simulation is useful in itself and has generated a variety of research questions whose answers have implications for the development of more cost-effective training programs.

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APPENDIX A

EQUIVALENCE BETWEEN COMMAND MEMORY REPRESENTATION AND A DIFFERENTIAL EQUATION REPRESENTATION OF THE TASK CONTROLLER

Any linear system (this restriction will be removed later) can be characterized by the vector equation

$$\dot{X} = AX + BU$$

where X is an n x 1 column vector of the state variables of the system

A is an n x n transition matrix

U is an n x 1 input vector

B is a 1 x n input weighting vector

$\dot{X}$ is the time derivative of X.

Approximating the derivative with a backward difference, the equation may be written

$$\frac{X(t_i) - X(t_{i-1})}{\Delta t} = AX(t_{i-1}) + BU(t_{i-1})$$

or

$$X(t_i) = X(t_{i-1}) + \Delta t \left[AX(t_{i-1}) + BU(t_{i-1})\right]$$

So, the state at time t_i is totally dependent of the state at time t_{i-1} and the input at t_{i-1}. This fact is the basis for the Command Memory. If the task controller input and output are observed/recorded at periodic intervals, a set of ordered pairs $X(t_i)$, $U(t_i)$ will be produced. This data can be mapped into a two-dimensional array such that the contents at location $X(t_i)$, $X(t_{i-1})$ is $U(t_{i-1})$.

To see how the restriction on system linearity may be removed, consider the following one-dimensional version of the system of equations discussed just above:

$$\dot{X} = AX + BU$$

Any non-linearity can be represented by making A and/or B a function of X or U, or both. As an example, making A a function of X and U:

$$\dot{X} = f(X,U) + BU$$

Approximating the derivative by a difference as before

$$\frac{X_i - X_{i-1}}{\Delta t} = f(X_{i-1}U_{i-1})X_{i-1} + BU_{i-1}$$

$$X_i = X_{i-1} + \Delta t\left[f(X_{i-1},U_{i-1})X_{i-1} + BU_{i-1}\right]$$

Again, by observing X_i and U_i at successive instants in time, an array can be filled by loading U_{i-1} at the location X_i, X_{i-1}. And, as before, by having this information available, effective control is possible even though the non-linearity is neither explicitly determined or recorded.

APPENDIX B

PROCEDURE FOR TRACK GENERATION

The track was generated by passing a pseudo-random signal through a low-pass filter as shown in Figure B-1. The low-pass filter has the characteristic that frequencies below a certain limit are passed through unattenuated while higher frequency components are heavily attenuated. The attenuation characteristic of the filters used to generate the $\frac{1}{4}$ Hz and $\frac{1}{2}$ Hz tracks (as they are called) are shown in Figures B-2 and B-3. The recursion relationships necessary to implement these attenuation characteristics are provided in Table B-1.

The pseudo-random signal generator was designed to produce, on the average, equal energy at all frequencies over a band broader than the corner frequencies of the low-pass filters. The algorithm for generating this function is presented in Table B-2. A test of how uniformly distributed the energy of the signal happens to be is provided by the auto-correlation function of the signal. A uniformly distributed signal will have an auto-correlation function as shown in Figure B-4. The actual computed auto-correlation function is shown in Figure B-5.

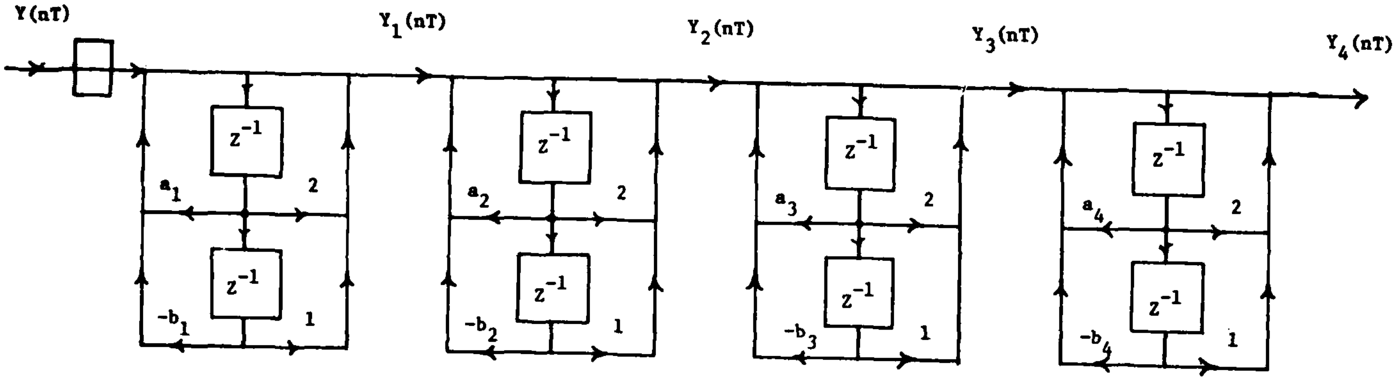

Figure B1. Block Diagram of 8th Order Butterworth Digital Filter

TABLE B-1

Butterworth Low-Pass Filter Realization

$$y_1(nT) = a_1y_1(n - 1)T - b_1y_1(n - 2)T + \{G\ x^*(nT) + 2x[(n - 1)T] + x[(n - 2)T]\}$$

$$y_2(nT) = a_2y_2[(n - 1)T] - b_2y_2(n - 2)T + y_1(nT) + 2y_1(n - 1)T + y_1(n - 2)T$$

$$y_3(nT) = a_3y_3(n - 1)T - b_3y_3(n - 2)T + y_2(nT) + 2y_2(n - 1)T + y_2(n - 2)T$$

$$y_4^*(nT) = a_4y_4(n - 1)T - b_4y_4(n - 2)T + y_3(nT) + 2y_3(n - 1)T + y_3(n - 2)T$$

	0.25 Hz	0.5 Hz
a_1, b_1	1.972, 0.976	1.936, 0.951
a_2, b_2	1.928, 0.932	1.856, 0.871
a_3, b_3	1.896, 0.899	1.796, 0.810
a_4, b_4	1.880, 0.884	1.766, 0.780
G	1×10^{-12}	1.723×10^{-10}
T	40 ms	40 ms

*x(nT) is the input signal; $y_4(nT)$ is the output signal

TABLE B-2

Algorithm for Generation of Pseudo-Random Signal for Forcing Function

In general,

$$N_i = AN_{i-1} \bmod B,$$

where N_i = current number

A = 99

B = 1097684

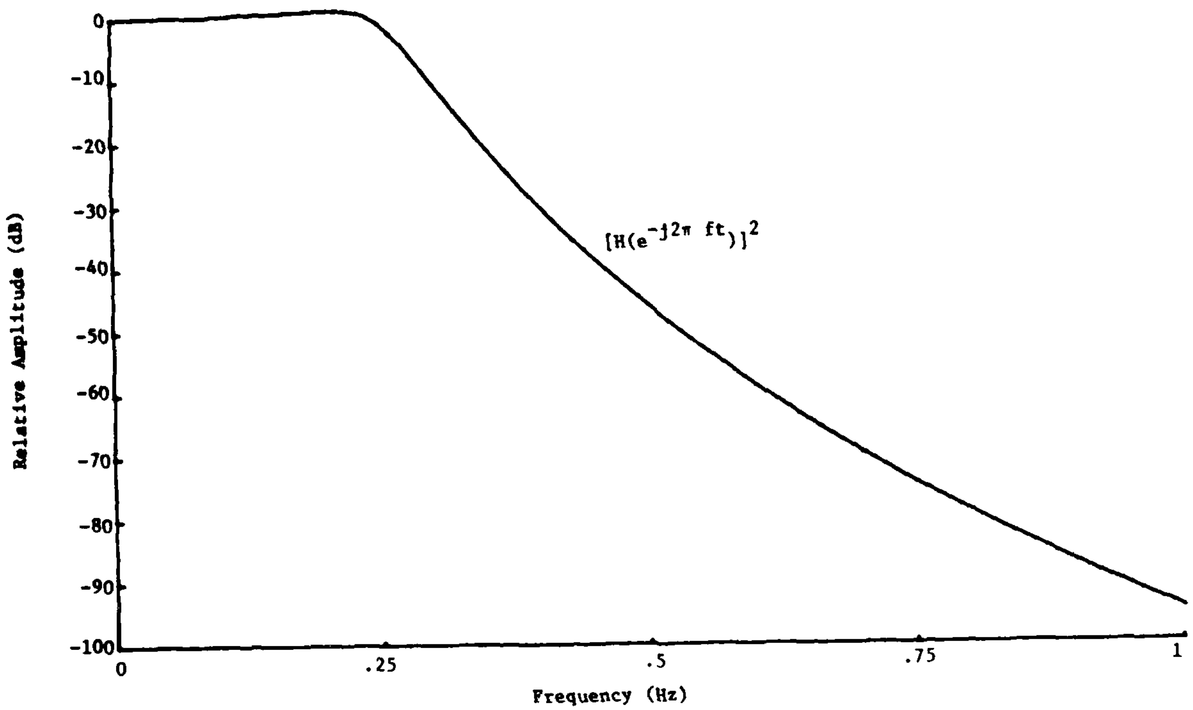

Figure B2. Frequency Response of 8th Order Butterworth Filter with .25 Hz Corner Frequencies

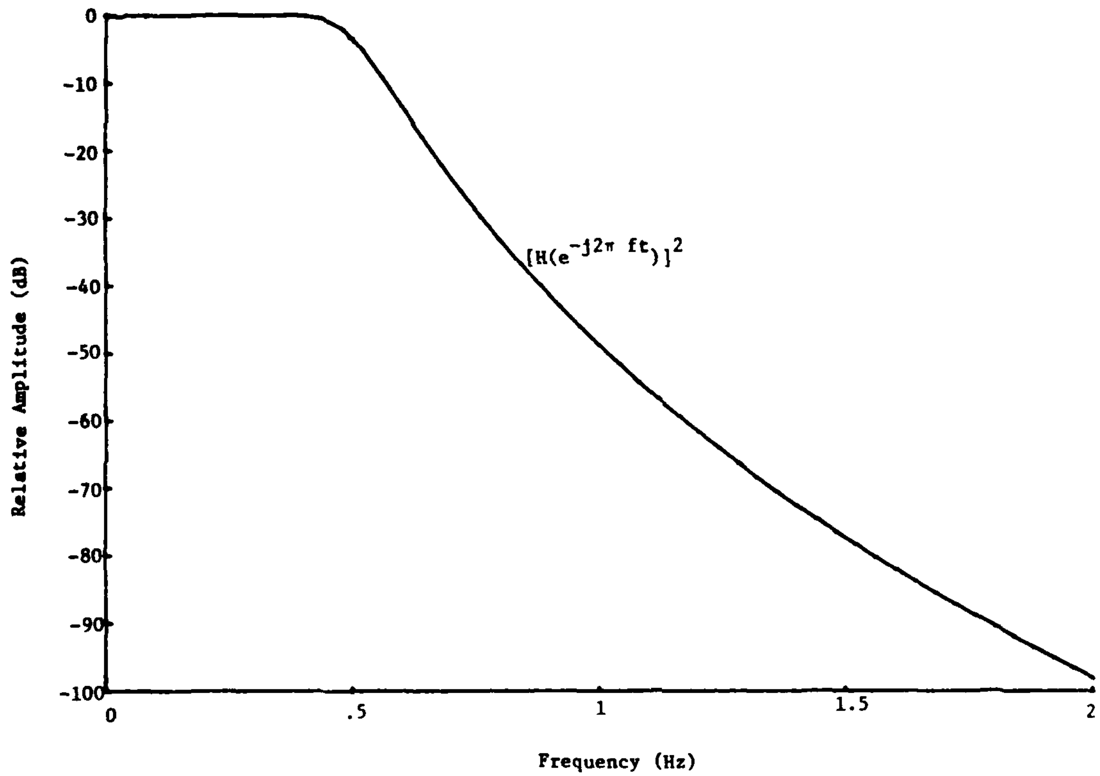

Figure B3. Frequency Response of 8th Order Butterworth Filter with .5 Hz Corner Frequencies

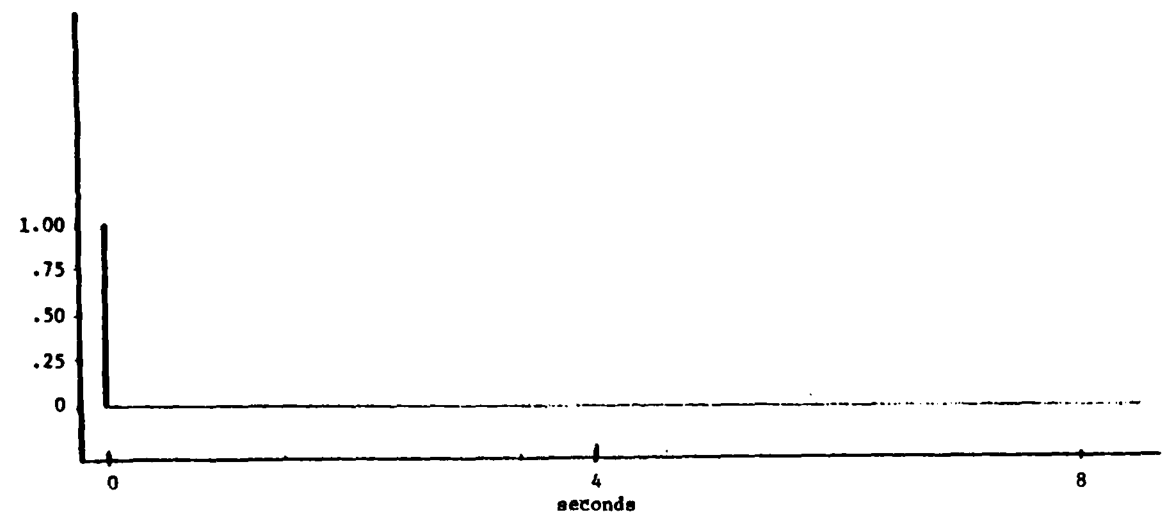

Figure B4. Ideal Autocorrelation Function for Bandlimited, Uniformly Distributed Noise

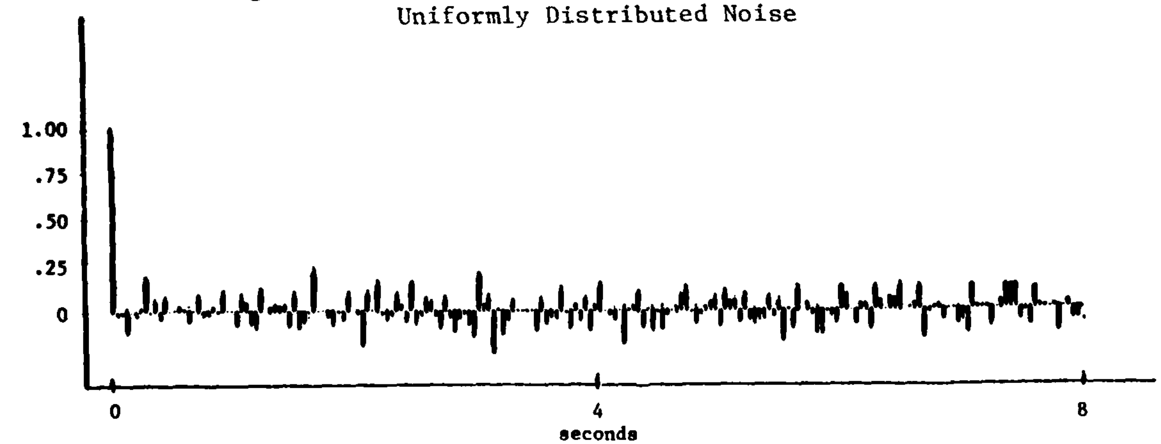

Figure B5. Actual Autocorrelation Function for Noise Source Used in Experiments

APPENDIX C

ALGORITHMS FOR NONLINEAR FIRST ORDER POSITION CONTROL USED IN PRELIMINARY TESTING

Abbreviations Used:

ACCOM	=	Actual Current Command (Control stick position)
RCPOUT	=	Real current plant output (Screen position on same scale as control stick position)
x_c	=	Transfer constant
X_c	=	.1

If 56 ACCOM 76, $X = X_c$, and go to Plant update

If 38 ACCOM 89, $X = \frac{X_c}{1.5}$, and go to Plant update

If 25 ACCOM 102, $X = \frac{X_c}{2.0}$, and go to Plant update

If 13 ACCOM 114, $X = \frac{X_c}{3.0}$, and go to Plant update

If 0 ACCOM 128, $X = \frac{X_c}{4.0}$, and go to Plant update

Plant update:

$$RCPOUT_{i+1} = RCPOUT_i + X\ (ACCOM - RCPOUT_i)$$

APPENDIX D

PRELIMINARY TEST OF USEFULNESS OF MASE
(MEAN ABSOLUTE STATE ERROR) FOR
CHOICE OF BEST-FIT MODELS TO HUMAN BEHAVIOR

I. Calculation of MASE Value

A. Derivation

As the model or operator attempt to track the road, the control stick position is recorded. A value is sampled every seconds. The value of is 40 ms. The values recorded are then stored for analysis and may be pictured as in Figure D-1.

$$X_1 \qquad X_2 \qquad \ldots \qquad X_i \qquad \ldots \qquad X_n$$

Figure D-1

where X is used to denote a position value. The data in this form provides only instantaneous position values.

We define velocity to be the following:

$$V_i = \frac{dX_i}{dt} = \frac{\Delta X}{\Delta} = \frac{X_i - X_{i-1}}{\Delta t}$$

That is, velocity is the change in position between samples divided by the time between samples.

Similarly, acceleration is defined:

$$A_i = \frac{dV_i}{dt} = \frac{\Delta V}{\Delta^2} = \frac{V_i - V_{i-1}}{\Delta^2 t}$$

The Absolute State Error (ASE) for each of the 500 points in a time bin is then defined as:

$$ASE_i = X_i + V_i + A_i$$

The Absolute State Error (MASE) is obtained by summing the individual state errors over all points in a bin and dividing the sum by the number of points.

II. Procedure for Comparing MASE, RMS, & Human Choices of Best-Fit Models to Human Behavior

A. A sample of 44 plots of model-human control stick position for Operator 1112, bin 51 was generated. This operator was tested in the ¼ Hz, narrow guideline condition. The sample of plots for bin 51 included:

- The 10 best models as chosen by MASE

- The 10 best models as chosen by RMS

- Every 4th model out of the total model set of 75 for that training condition

- Model numbers that clustered around the models chosen by MASE and/or RMS. These models are similar to those chosen by MASE and RMS and are, therefore possible candidates for best-fit model. However, models with ADJUST values of 50 were excluded, as these models are obviously not good fits to human control stick data.

B. Six people were asked to choose and rank the 10 best-fit models from the sample of 44.

C. A comparison was made between the best fit models chosen by people, and those picked by MASE and/or RMS (see Table D-1). For each person, each model picked was labeled R (picked by RMS only), M (picked by MASE only), or RM (picked by both RMS and MASE). The agreement in relative rankings between statistic and human choices was not considered in this preliminary analysis. However, relative agreement in ranking between humans was examined.

D. The results indicated that neither MASE nor RMS was very consistent with human choice of the 10 best-fit models. For most human listings, there was some overlap with MASE choices and some with RMS choices, with a tendency for there to be greater overlap between RMS and human choices than between MASE and human choices. Human subjects did not agree with one another in their relative rankings of the 10 best model fits (see Table D-2).

MASE and RMS agreed in five out of the ten models picked as ten best, and agreed in their first choice. This choice, of model 34, was the first choice of only one of the persons (HE), however.

TABLE D-1

CHOICES OF TEN BEST-Fit MODELS BY MASE, RMS, AND SUBJECTS

Model Rank	MASE	RMS	Subjects DM	BB	HE	BS	FV	DF
1	34	34	30R	31RM	34RM	31RM	73 M	31R
2	70*	19*	29R	34RM	37RM	19R	34RM	40R
3	49	37	31RM	19R	49RM	49RM	67 M	37RM
4	37	31	34RM	37RM	19R	30R	49RM	19 M
5	73*	40*	19R	70 M	73 M	70 M	70 M	34RM
6	46	29*	73 M	49RM	67 M	40R	52 M	30R
7	31	49	37RM	29R	40R	34RM	37RM	29R
8	67*	28*	70 M	67 M	59	37RM	75	25
9	52*	30*	49RM	40R	31RM	44	31RM	70 M
10	61*	46	25	30R	74	23	19R	44

*Picked by MASE or RMS.

Overlap (# of Models Chosen By Both) Between Subjects and RMS, Subjects and MASE

Subject	Agree With MASE Only	Agree With RMS ONLY	Agree With Both	Other
DM	2	3	4	1
BB	2	4	4	0
HE	2	2	4	2
BS	1	3	4	2
FV	4	1	4	1
DF	2	4	2	2

TABLE D-2

RANKS ASSIGNED TO EACH MODEL BY SUBJECTS

Model	Subjects					
	DM	BB	HE	BS	FV	DF
19	5	3	4	2	10	4
23				10		
25	10					8
28						
29	2	7				7
30	1	10		4		6
31	3	1	9	1	9	1
34	4	2	1	7	2	5
37	7	4	2	8	7	3
40		9	7	6		2
44				9		10
46						
49	9	6	3	3	4	
52					6	
59			8			
61						
67		8	6		3	
70	8	5		5	5	9
73	6		5		1	
74			10			
75					8	

APPENDIX E

DATA MATRICES FOR ONE SUBJECT
IN 1/4 HZ TRACK CONDITION

Matrix 1. FOR ALL TIME BINS, TEN BEST-FIT MODELS (BY NUMBER) AND THEIR ASSOCIATED RMS DIFFERENCES (IN ARBITRARY UNITS)*

QUASOR BH-TQGI-BTNGO
OPERATOR IDENTIFICATION NUMBER: 1111

TIME BIN DOWN	1 RMS	ID	2 RMS	ID	3 RMS	ID	4 MASE	ID	5 RMS	ID
1	11.38	46	11.39	61	11.49	16	12.24	48	12.32	31
2	8.44	46	8.97	49	9.67	72	9.79	64	9.81	61
3	9.83	61	10.63	64	10.07	46	10.13	67	10.63	49
4	7.20	61	7.53	46	7.70	34	7.84	65	7.84	64
5	9.22	61	9.49	64	9.75	46	10.11	67	10.21	49
6	7.72	46	7.73	61	8.00	67	8.37	64	8.52	49
7	7.43	22	7.88	47	7.93	46	8.00	32	8.09	61
8	8.51	61	8.90	46	9.25	64	9.52	31	9.78	49
9	6.49	61	6.65	46	6.80	65	7.13	31	7.25	64
10	9.08	64	9.26	22	9.40	49	9.49	37	9.51	52
11	8.45	50	9.49	65	9.70	46	9.73	64	10.00	61
12	13.36	49	13.94	46	14.28	37	14.34	31	14.51	34
13	8.46	25	8.54	52	8.95	64	9.20	61	9.44	34
14	9.41	67	9.41	46	9.44	49	9.82	22	10.09	61
15	11.45	19	12.21	22	12.49	61	12.51	16	12.53	36
16	9.12	48	9.13	46	9.36	67	9.41	61	9.49	62
17	11.26	65	11.69	18	11.77	46	11.97	63	12.01	50
18	11.83	30	11.89	19	11.96	61	12.08	47	12.10	22
19	8.61	47	8.73	63	8.98	18	9.25	49	9.40	17
20	9.35	46	9.69	49	9.85	24	9.96	50	10.25	62
21	6.00	46	6.08	61	6.14	34	6.21	31	6.28	67
22	7.45	22	7.93	61	8.16	19	8.30	64	8.50	49
23	8.17	48	8.55	33	8.69	62	9.04	36	9.18	47
24	11.57	46	11.60	49	11.60	61	11.80	22	12.06	50
25	6.06	64	6.11	61	6.11	37	6.16	52	6.32	26
26	6.99	31	7.23	34	7.27	46	7.30	49	7.42	61
27	8.67	17	8.77	47	8.80	23	8.91	46	8.95	50
28	6.30	46	6.44	25	6.49	50	6.66	47	7.03	65
29	7.41	61	7.55	64	7.82	46	7.99	47	8.15	31
30	6.16	19	6.51	38	6.56	46	6.60	49	6.70	31
31	8.78	50	8.98	63	9.11	47	9.18	49	9.21	36
32	6.68	64	7.16	49	7.18	46	7.24	61	7.50	35
33	5.81	61	5.91	46	6.34	49	6.35	31	6.36	50
34	8.18	61	8.21	49	8.37	46	8.53	64	9.19	31
35	9.24	64	9.29	50	9.83	33	10.02	63	10.04	49
36	9.58	61	10.01	46	10.73	50	11.26	49	11.45	48
37	5.65	34	5.70	67	5.70	46	5.92	64	6.02	61
38	5.73	61	6.69	64	6.75	46	6.82	16	6.84	34
39	7.47	25	7.61	50	7.74	61	7.92	19	7.96	30
40	6.32	47	6.61	33	6.77	35	7.06	48	7.10	18
41	7.55	47	8.24	18	8.50	32	8.55	36	8.59	62
42	5.95	19	6.15	61	6.28	37	6.34	38	6.39	29
43	6.05	46	6.41	47	6.44	61	6.47	31	6.57	66
44	7.05	64	7.16	49	7.18	31	7.47	61	7.54	38
45	8.04	61	8.09	62	8.11	46	8.26	31	8.42	34
46	7.11	31	7.54	34	7.87	61	7.90	25	8.11	28
47	8.69	62	9.21	48	9.92	32	9.97	47	10.02	66
48	9.17	61	9.27	46	9.72	49	9.84	31	10.04	22
49	5.31	46	5.83	64	5.87	52	6.08	61	6.18	37
50	6.07	50	6.38	61	6.53	31	6.60	48	6.64	46
51	7.12	25	7.27	26	7.41	38	7.45	47	7.56	23
52	5.83	50	6.21	48	6.22	51	6.50	32	6.60	47
53	8.41	65	8.46	49	8.72	62	8.83	48	8.97	50
54	5.74	49	5.94	34	6.08	61	6.09	50	6.21	31
55	7.49	31	7.71	62	7.90	47	7.98	36	7.99	63
56	6.68	49	6.77	64	6.81	61	6.88	30	7.00	22
57	4.92	47	5.01	46	5.23	62	5.40	31	5.42	61
58	6.27	34	6.31	61	6.43	28	6.85	49	6.89	31
59	7.58	17	7.76	47	7.78	51	7.81	62	7.85	32
60	27.32	25	27.73	68	27.80	49	27.83	37	27.84	40

* One unit is equivalent to .29 cm.

Matrix 1. FOR ALL TIME BINS, TEN BEST-FIT MODELS (BY NUMBER) AND THEIR ASSOCIATED RMS DIFFERENCES (IN ARBITRARY UNITS)* (CONCLUDED)

6 RMS	ID	7 RMS	ID	8 RMS	ID	9 RMS	ID	10 RMS	ID
12.47	64	12.50	47	12.68	19	13.15	22	13.29	49
10.57	31	10.59	55	10.87	37	10.97	65	10.98	22
10.65	31	11.25	56	11.43	1	11.56	34	11.88	19
7.96	67	8.05	31	8.26	49	8.52	16	8.89	22
10.38	53	10.63	31	10.76	22	10.77	65	11.06	34
8.65	19	8.74	65	8.84	16	8.98	31	9.10	34
8.32	49	8.59	19	8.60	64	8.62	50	8.70	23
9.80	67	9.83	22	9.95	52	10.00	4	10.01	66
7.54	23	7.58	50	7.63	19	7.65	41	7.78	32
9.68	71	9.72	61	9.88	46	10.07	67	10.11	40
10.56	31	10.80	16	10.90	49	11.10	34	11.17	67
14.97	67	15.07	64	15.21	61	15.33	52	15.37	22
9.51	37	9.65	46	9.78	31	9.86	26	9.90	35
10.16	50	10.17	70	10.22	64	10.45	31	10.54	37
12.62	20	12.76	31	12.83	24	12.86	38	12.98	29
9.70	47	9.74	52	9.96	23	9.97	19	9.98	38
12.08	62	12.08	51	12.20	6	12.40	35	12.42	47
12.22	25	12.35	67	12.44	46	12.48	40	12.53	23
9.47	19	9.49	61	9.55	50	9.73	1	9.89	16
10.27	22	10.30	27	10.35	61	10.45	31	10.48	52
6.35	64	6.43	49	6.44	68	6.59	65	6.64	16
8.59	27	8.62	52	8.75	28	8.82	29	8.87	30
9.45	17	9.65	20	9.66	21	9.86	50	9.94	1
12.35	16	12.46	34	12.46	31	12.51	64	12.70	67
6.33	46	6.42	31	6.49	30	6.58	67	6.60	49
7.54	22	7.87	30	7.99	19	8.07	29	8.10	25
9.02	62	9.11	51	9.21	61	9.50	33	9.52	49
7.09	48	7.15	61	7.34	17	7.37	62	7.38	16
8.16	65	8.41	35	8.46	19	8.48	50	8.60	33
6.82	47	6.87	29	6.87	22	6.87	30	6.89	34
9.25	19	9.26	22	9.32	46	9.52	17	9.58	27
7.58	62	7.94	34	8.00	19	8.26	20	8.34	31
6.43	47	6.45	51	6.60	32	6.67	19	6.70	22
9.30	34	9.31	52	9.33	19	9.42	37	9.49	22
10.39	61	10.44	51	10.45	46	10.74	22	10.82	16
11.49	65	11.70	62	11.77	24	11.85	35	12.00	36
6.12	52	6.18	50	6.21	49	6.22	35	6.27	31
6.85	65	6.98	22	7.06	48	7.07	49	7.18	50
8.04	20	8.11	49	8.12	26	8.13	29	8.16	64
7.33	32	7.34	62	7.46	69	7.55	51	7.58	46
8.63	51	8.64	17	8.73	48	8.77	50	8.85	61
6.40	49	6.48	64	6.54	67	6.56	51	6.60	30
6.70	50	6.92	63	7.01	35	7.04	65	7.10	34
7.62	50	7.77	46	7.92	52	8.00	34	8.19	30
8.44	50	8.46	32	8.49	16	8.54	64	8.56	47
8.35	29	8.35	27	8.41	46	8.42	30	8.44	35
10.20	35	10.27	33	10.33	61	10.34	51	10.68	50
10.10	1	10.23	50	10.34	38	10.44	40	10.47	32
6.19	34	6.24	31	6.28	49	6.33	19	6.40	50
6.74	47	6.88	34	6.89	65	6.92	49	6.97	64
7.57	19	7.58	46	7.59	31	7.74	22	7.78	34
6.60	66	6.61	62	6.64	33	6.65	49	6.83	67
9.01	51	9.10	63	9.23	47	9.25	5	9.27	32
6.31	64	6.35	47	6.50	19	6.56	67	6.60	30
8.06	66	8.06	46	8.08	49	8.18	50	8.30	1
7.06	19	7.21	29	7.26	47	7.34	31	7.38	34
5.43	50	5.47	64	5.53	32	5.55	34	5.65	16
7.06	30	7.06	29	7.08	25	7.14	46	7.17	22
8.04	49	8.31	20	8.61	48	8.69	39	8.70	1
27.89	38	28.00	34	28.01	46	28.14	64	28.17	54

* One unit is equivalent to .29 cm.

Matrix 2. FOR ALL TIME BINS, CONTROL STRATEGY PARAMETER VALUES (UNITS SPECIFIED FOR THE SIMULATION HOPE)** FOR THE TEN BEST-FIT MODELS

PARAT BH-TQGI-BTNGO

OPERATOR IDENTIFICATION NUMBER: 1111

TIME BIN DOWN	COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ
1	4	2	2	5	2	2	2	2	2	4	2	8	3	2	2
2	4	2	2	4	4	2	5	16	8	5	4	2	5	2	2
3	5	2	2	5	4	2	4	2	2	5	8	2	4	4	2
4	5	2	2	4	2	2	3	4	2	5	4	5	5	4	2
5	5	2	2	5	4	2	4	2	2	5	8	2	4	4	2
6	4	2	2	5	2	2	5	8	2	5	4	2	4	4	2
7	2	8	2	4	2	5	4	2	2	3	2	5	5	2	2
8	5	2	2	4	2	2	5	4	2	3	2	2	4	4	2
9	5	2	2	4	2	2	5	4	5	3	2	2	5	4	2
10	5	4	2	2	8	2	4	4	2	3	8	2	4	8	2
11	4	4	5	5	4	5	4	2	2	5	4	2	5	2	2
12	4	4	2	4	2	2	3	8	2	3	2	2	3	4	2
13	2	16	2	4	8	2	5	4	2	5	2	2	3	4	2
14	5	8	2	4	2	2	4	4	2	2	8	2	5	2	2
15	2	4	2	2	8	2	5	2	2	2	2	2	3	4	8
16	4	2	8	4	2	2	5	8	2	5	2	2	5	2	5
17	5	4	5	2	2	8	4	2	2	5	2	8	4	4	5
18	2	32	8	2	4	2	5	2	2	4	2	5	2	8	2
19	4	2	5	5	2	8	2	2	8	4	4	2	2	2	5
20	4	2	2	4	4	2	2	8	8	4	4	5	5	2	5
21	4	2	2	5	2	2	3	4	2	3	2	2	5	8	2
22	2	8	2	5	2	2	2	4	2	5	4	2	4	4	2
23	4	2	8	3	2	8	5	2	5	3	4	8	4	2	5
24	4	2	2	4	4	2	5	2	2	2	8	2	4	4	5
25	5	4	2	5	2	2	3	8	2	4	8	2	2	16	5
26	3	2	2	3	4	2	4	2	2	4	4	2	5	2	2
27	2	2	5	4	2	5	2	8	5	4	2	2	4	4	5
28	4	2	2	2	16	2	4	4	5	4	2	5	5	4	5
29	5	2	2	5	4	2	4	2	2	4	2	5	3	2	2
30	2	4	2	3	8	5	4	2	2	4	4	2	3	2	2
31	4	4	5	5	2	8	4	2	5	4	4	2	3	4	8
32	5	4	2	4	4	2	4	2	2	5	2	2	3	4	5
33	5	2	2	4	2	2	4	4	2	3	2	2	4	4	5
34	5	2	2	4	4	2	4	2	2	5	4	2	3	2	2
35	5	4	2	4	4	5	3	2	8	5	2	8	4	4	2
36	5	2	2	4	2	2	4	4	5	4	4	2	4	2	8
37	3	4	2	5	8	2	4	2	2	5	4	2	5	2	2
38	5	2	2	5	4	2	4	2	2	2	2	2	3	4	2
39	2	16	2	4	4	5	5	2	2	2	4	2	2	32	8
40	4	2	5	3	2	8	3	4	5	4	2	8	2	2	8
41	4	2	5	2	2	8	3	2	5	3	4	8	5	2	5
42	2	4	2	5	2	2	3	8	2	3	8	5	2	32	5
43	4	2	2	4	2	5	5	2	2	3	2	2	5	4	8
44	5	4	2	4	4	2	3	2	2	5	2	2	3	8	5
45	5	2	2	5	2	5	4	2	2	3	2	2	3	4	2
46	3	2	2	3	4	2	5	2	2	2	16	2	2	32	2
47	5	2	5	4	2	8	3	2	5	4	2	5	5	4	8
48	5	2	2	4	2	2	4	4	2	3	2	2	2	8	2
49	4	2	2	5	4	2	4	8	2	5	2	2	3	8	2
50	4	4	5	5	2	2	3	2	2	4	2	8	4	2	2
51	2	16	2	2	16	5	3	8	5	4	2	5	2	8	5
52	4	4	5	4	2	8	4	4	8	3	2	5	4	2	5
53	5	4	5	4	4	2	5	2	5	4	2	8	4	4	5
54	4	4	2	3	4	2	5	2	2	4	4	5	3	2	2
55	3	2	2	5	2	5	4	2	5	3	4	8	5	2	8
56	4	4	2	5	4	2	5	2	2	2	32	8	2	8	2
57	4	2	5	4	2	2	5	2	5	3	2	2	5	2	2
58	3	4	2	5	2	2	2	32	2	4	4	2	3	2	2
59	2	2	5	4	2	5	4	4	8	5	2	5	3	2	5
60	2	16	2	5	8	5	4	4	2	3	8	2	3	16	2

**COTs of 1,2,3,4, and 5 correspond to 40,80,120,160, and 200 msec
ERRLIMs of 2,4,8,16,32 correspond to .58, 1.17, 2.34, 4.67 and 9.35 cm
ADJUSTs of 2,5,8 correspond to .58, 1.46, and 2.34 cm

Matrix 2. FOR ALL TIME BINS, CONTROL STRATEGY PARAMETER VALUES (UNITS SPECIFIED FOR THE SIMULATION HOPE)** FOR THE TEN BEST-FIT MODELS (CONCLUDED)

COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ	COT	ER	ADJ
5	4	2	4	2	5	2	4	2	2	8	2	4	4	2
3	2	2	4	16	2	3	8	2	5	4	5	2	8	2
3	2	2	4	16	5	1	2	2	3	4	2	2	4	2
5	8	2	3	2	2	4	4	2	2	2	2	2	8	2
4	8	5	3	2	2	2	8	2	5	4	5	3	4	2
2	4	2	5	4	5	2	2	2	3	2	2	3	4	2
4	4	2	2	4	2	5	4	2	4	4	5	2	8	5
5	8	2	2	8	2	4	8	2	1	4	2	5	4	8
2	8	5	4	4	5	2	4	2	3	16	5	3	2	5
5	16	5	5	2	2	4	2	2	5	8	2	3	16	2
3	2	2	2	2	2	4	4	2	3	4	2	5	8	2
5	8	2	5	4	2	5	2	2	4	8	2	2	8	2
3	8	2	4	2	2	3	2	2	2	16	5	3	4	5
4	4	5	5	16	2	5	4	2	3	2	2	3	8	2
2	4	5	3	2	2	2	8	8	3	8	5	2	32	5
4	2	5	4	8	2	2	8	5	2	4	2	3	8	5
5	2	5	4	4	8	1	4	8	3	4	5	4	2	5
2	16	2	5	8	2	4	2	2	3	16	2	2	8	5
2	4	2	5	2	2	4	4	5	1	2	2	2	2	2
2	8	2	2	16	8	5	2	2	3	2	2	4	8	2
5	4	2	4	4	2	5	8	5	5	4	5	2	2	2
2	16	8	4	8	2	2	32	2	2	32	5	2	32	8
2	2	5	2	4	5	2	4	8	4	4	5	1	2	2
2	2	2	3	4	2	3	2	2	5	4	2	5	8	2
4	2	2	3	2	2	2	32	8	5	8	2	4	4	2
2	8	2	2	32	8	2	4	2	2	32	5	2	16	2
5	2	5	4	4	8	5	2	2	3	2	8	4	4	2
4	2	8	5	2	2	2	2	5	5	2	5	2	2	2
5	4	5	3	4	5	2	4	2	4	4	5	3	2	8
4	2	5	2	32	5	2	8	2	2	32	8	3	4	2
2	4	2	2	8	2	4	2	2	2	2	5	2	16	8
5	2	5	3	4	2	2	4	2	2	4	5	3	2	2
4	2	5	4	4	8	3	2	5	2	4	2	2	8	2
3	4	2	4	8	2	2	4	2	3	8	2	2	8	2
5	2	2	4	4	8	4	2	2	2	8	2	2	2	2
5	4	5	5	2	5	2	8	8	3	4	5	3	4	8
4	8	2	4	4	5	4	4	2	3	4	5	3	2	2
5	4	5	2	8	2	4	2	8	4	4	2	4	4	5
2	4	5	4	4	2	2	16	5	2	32	5	5	4	2
3	2	5	5	2	5	5	8	8	4	4	8	4	2	2
4	4	8	2	2	5	4	2	8	4	4	5	5	2	2
4	4	2	5	4	2	5	8	2	4	4	8	2	32	8
4	4	5	5	2	8	3	4	5	5	4	5	3	4	2
4	4	5	4	2	2	4	8	2	3	4	2	2	32	8
4	4	5	3	2	5	2	2	2	5	4	2	4	2	5
2	32	5	2	16	8	4	2	2	2	32	8	3	4	5
3	4	5	3	2	8	5	2	2	4	4	8	4	4	5
1	2	2	4	4	5	3	8	5	3	16	2	3	2	5
3	4	2	3	2	2	4	4	2	2	4	2	4	4	5
4	2	5	3	4	2	5	4	5	4	4	2	5	4	2
2	4	2	4	2	2	3	2	2	2	8	2	3	4	2
5	4	8	5	2	5	3	2	8	4	4	2	5	8	2
4	4	8	5	2	8	4	2	5	1	4	5	3	2	5
5	4	2	4	2	5	2	4	2	5	8	2	2	32	8
5	4	8	4	2	2	4	4	2	4	4	5	1	2	2
2	4	2	2	32	5	4	2	5	3	2	2	3	4	2
4	4	5	5	4	2	3	2	5	3	4	2	2	2	2
2	32	8	2	32	5	2	16	2	4	2	2	2	8	2
4	4	2	2	4	5	4	2	8	3	8	8	1	2	2
3	8	5	3	4	2	4	2	2	5	4	2	4	8	8

**COTs of 1,2,3,4, and 5 correspond to 40,80,120,160, and 200 msec
ERRLIMs of 2,4,8,16,32 correspond to .58, 1.17, 2.34, 4.67 and 9.35 cm
ADJUSTs of 2,5,8 correspond to .58, 1.46, and 2.34 cm